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# **statistics in speech recognition Finite-state models, event logics and**

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Julie Carson -Berndsen

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Finite-state models, event logics and ite-state models, event logics and<br>statistics in speech recognition

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statistics in speech recognition<br>BY JULIE CARSON-BERNDSEN

BY JULIE CARSON-BERNDSEN<br> *Department of Computer Science, University College Dublin, BERNDSE*<br>*Pomputer Science, University C*<br>*Belfield, Dublin 4, Ireland*  $Belfield, Dublin 4, Ireland$ <br>This paper presents a constraint-based approach to speech recognition which com-

This paper presents a constraint-based approach to speech recognition which com-<br>bines aspects of event logic with efficient processing strategies. Although stochastic<br>approaches are currently at the forefront of speech-re This paper presents a constraint-based approach to speech recognition which com-<br>bines aspects of event logic with efficient processing strategies. Although stochastic<br>approaches are currently at the forefront of speech-re bines aspects of event logic with efficient processing strategies. Although stochastic approaches are currently at the forefront of speech-recognition applications, it has now been recognized that linguistic structure is r approaches are currently at the forefront of speech-recognition applications, it has<br>now been recognized that linguistic structure is required in order to deal with the<br>problem of recognizing new words. The computational l here of recognized that linguistic structure is required in order to deal with the problem of recognizing new words. The computational linguistic approach presented here offers solutions to the problems of how to process w problem of recognizing new words. The computational linguistic approach presented<br>here offers solutions to the problems of how to process words which have not been<br>heard before, and how to develop fine-grained knowledge re here offers solutions to the problems of how to process words which have not been<br>heard before, and how to develop fine-grained knowledge representation and process-<br>ing techniques for linguistic units smaller than the wor heard before, and how to develop fine-grained knowledge representation and processing techniques for linguistic units smaller than the word. Furthermore, it is investigated how statistical data can be integrated into the p ing techniques for linguistic units smaller than the word. Furthermore, it is investigated how statistical data can be integrated into the phonological constraint model<br>in order to minimize the discrepancy between expectat gated how statistical data can be<br>in order to minimize the discrepar<br>constraints and the actual data.<br>Keywords: finite-state technic

constraints and the actual data.<br>Keywords: finite-state techniques; multilinearity; events; speech recognition

### 1. Introduction

1. Introduction<br>One of the major problems in the area of speech technology concerns the treatment<br>of new words. In general, a new word refers to any structure that is well-formed with One of the major problems in the area of speech technology concerns the treatment<br>of new words. In general, a new word refers to any structure that is well-formed with<br>respect to the phonological and morphological constrai One of the major problems in the area of speech technology concerns the treatment<br>of new words. In general, a new word refers to any structure that is well-formed with<br>respect to the phonological and morphological constrai of new words. In general, a new word refers to any structure that is well-formed with<br>respect to the phonological and morphological constraints of a particular language<br>but which is not part of a lexicon of that language. respect to the phonological and morphological constraints of a particular language<br>but which is not part of a lexicon of that language. For example, the word *blant* is<br>not found in any English lexicon, but a native speake but which is not part of a lexicon of that language. For example, the word *blant* is<br>not found in any English lexicon, but a native speaker of the language would con-<br>sider it to be well-formed (as opposed to a form such not found in any English lexicon, but a native speaker of the language would consider it to be well-formed (as opposed to a form such as *bnanlt*, which is considered ill-formed). Such forms point to idiosyncratic gaps in sider it to be well-formed (as opposed to a form such as *bnanlt*, which is considered<br>ill-formed). Such forms point to idiosyncratic gaps in the lexicon and, thus, could<br>potentially become words of the language in the fut

ill-formed). Such forms point to idiosyncratic gaps in the lexicon and, thus, could<br>potentially become words of the language in the future. In the context of speech<br>recognition, the term 'new word' is usually restricted to potentially become words of the language in the future. In the context of speech<br>recognition, the term 'new word' is usually restricted to mean new with respect to<br>a particular corpus. While treatment of this phenomenon is for the model presented in this paper, the model itself assumes the model presented in this paper, the model itself assumes the broader definition of new words to refer to potential forms not included in the lexicon of the a particular corpus. While treatment of this phenomenon is one of the motivations<br>for the model presented in this paper, the model itself assumes the broader defi-<br>nition of new words to refer to potential forms not includ language. nition of new words to refer to potential forms not included in the lexicon of the language.<br>In order to recognize or generate new words, information about their internal

language.<br>In order to recognize or generate new words, information about their internal<br>structure is required. It is now generally accepted that morphological and phono-<br>logical constraints are required either implicitly ( In order to recognize or generate new words, information about their internal structure is required. It is now generally accepted that morphological and phonological constraints are required either implicitly (as in hidden structure is required. It is now generally accepted that morphological and phono-<br>logical constraints are required either implicitly (as in hidden Markov models) or<br>explicitly, in speech-technology applications. While ther logical constraints are required either implicitly (as in hidden Markov models) or explicitly, in speech-technology applications. While there is no doubt that stochastic approaches to speech recognition are at the forefron explicitly, in speech-technology applications. While there is no doubt that stochastic approaches to speech recognition are at the forefront of current research and form the basis of most commercial applications, Smolensky tic approaches to speech recognition are at the forefront of current research and<br>form the basis of most commercial applications, Smolensky (1999) has pointed out<br>that 'the potential for phonological theory to improve the that 'the potential for phonological theory to improve the performance of speech-<br>recognition systems remains largely unrealized'. This paper describes the *Time Map* 

1256  $J.$  *Carson-Berndsen*<br>model, a computational model of phonological interpretation for speech-recognition model, a computational model of phonological interpretation for speech-recognition<br>applications developed by the author since the early 1990s and recently reported in<br>Carson-Berndsen (1998). model, a computational m<br>applications developed by<br>Carson-Berndsen (1998).<br>The *Time Man* model us plications developed by the author since the early 1990s and recently reported in<br>
arson-Berndsen (1998).<br>
The *Time Map* model uses finite-state methodology and an event logic to demon-<br>
The *Time Map* model uses finite-s

Carson-Berndsen (1998).<br>The *Time Map* model uses finite-state methodology and an event logic to demonstrate how declarative descriptions of phonological constraints can play a role in speech recognition (see also Wagner The *Time Map* model uses finite-state methodology and an event logic to demonstrate how declarative descriptions of phonological constraints can play a role in speech recognition (see also Wagner (1997) for a speech-synth speech recognition (see also Wagner (1997) for a speech-synthesis application). The main aim of the work has not been to build a speech-recognition system that can speech recognition (see also Wagner (1997) for a speech-synthesis application). The<br>main aim of the work has not been to build a speech-recognition system that can<br>compete with stochastic systems in terms of system perform main aim of the work has not been to build a speech-recognition system that can<br>compete with stochastic systems in terms of system performance, but, rather, to<br>design a knowledge-based multilinear component for a speech-re design a knowledge-based multilinear component for a speech-recognition system<br>that uses phonological well-formedness constraints and which is demonstrably of design a knowledge-based multilinear component for a speech-recognition system<br>that uses phonological well-formedness constraints and which is demonstrably of<br>value in recognizing new words, modelling and investigating coa that uses phonological well-formedness constraints and which is demonstrably of value in recognizing new words, modelling and investigating coarticulation effects (temporal overlap of properties), and dealing with underspe value in recognizing new words, modelling and investigating coarticulation effects (temporal overlap of properties), and dealing with underspecified structures. The long-term goal of this work is, therefore, to provide a l (temporal overlap of properties), and dealing with underspecified structures. The<br>long-term goal of this work is, therefore, to provide a linguistic basis for integrating<br>symbolic and stochastic approaches to speech recogn long-term goal of this work is, therefore, to provide a linguistic basis for integrating<br>symbolic and stochastic approaches to speech recognition. While initial research on<br>this model has concentrated purely on the symboli symbolic and stochastic approaches to speech recognition. While initial research on<br>this model has concentrated purely on the symbolic approach, it has already been<br>demonstrated that the explicit incorporation of phonologi this model has concentrated purely on the symbolic approach, it has already been demonstrated that the explicit incorporation of phonological knowledge can provide useful structural constraints for the fine tuning of stoch useful structural constraints for the fine tuning of stochastic models (Jusek *et al.* 1994). The penultimate section of this paper investigates the extent to which statistical information can be integrated into the symbol 1994). The penultimate sect<br>tistical information can be is<br>application-specific tuning.<br>The main motivation for t tical information can be integrated into the symbolic model for the purposes of plication-specific tuning.<br>The main motivation for the *Time Map* approach to speech recognition concerns a compositionality and variability o

application-specific tuning.<br>The main motivation for the *Time Map* approach to speech recognition concerns<br>the compositionality and variability of spoken language, which can only be catered<br>for to a limited extent by con The main motivation for the *Time Map* approach to speech recognition concerns<br>the compositionality and variability of spoken language, which can only be catered<br>for to a limited extent by concatenative models, which assu for to a limited extent by concatenative models, which assume a rigid segmentation into non-overlapping units at some level of granularity (e.g. diphones, phonemes, for to a limited extent by concatenative models, which assume a rigid segmentation<br>into non-overlapping units at some level of granularity (e.g. diphones, phonemes,<br>demi-syllables, syllables). When dealing with speech reco into non-overlapping units at some level of granularity (e.g. diphones, phonemes, demi-syllables, syllables). When dealing with speech recognition, inputs are not in the form of discrete non-overlapping elements, as is usu demi-syllables, syllables). When dealing with speech recognition, inputs are not in the<br>form of discrete non-overlapping elements, as is usual in written language processing,<br>rather they are lattices containing competing h form of discrete non-overlapping elements, as is usual in written language processing,<br>rather they are lattices containing competing hypotheses and possibly conjunctions<br>in the case of overlapping information. The treatme rather they are lattices containing competing hypotheses and possibly conjunctions<br>in the case of overlapping information. The treatment of such gaps and overlaps in<br>the input lattice is required at all levels of processin in the case of overlapping information. The treatment of such gaps and overlaps in<br>the input lattice is required at all levels of processing and is termed the *lattice-to-*<br>*chart* problem. Furthermore, the predictive skil the input lattice is required at all levels of processing and is termed the *lattice-to-*<br>chart problem. Furthermore, the predictive skill of the native speaker of a language,<br>which allows the projection of a finite set of chart problem. Furthermore, the predictive skill of the native speaker of a language, which allows the projection of a finite set of actual structures onto a possibly infinite set of potential (well-formed) structures, mus which allows the projectio<br>set of potential (well-form<br>problem is to be solved.<br>The *Time Man* model c t of potential (well-formed) structures, must also be addressed if the 'new-word'<br>oblem is to be solved.<br>The *Time Map* model of phonological interpretation assumes lattices of acoustic-<br>onetic events as input and uses par

problem is to be solved.<br>The *Time Map* model of phonological interpretation assumes lattices of acoustic-<br>phonetic events as input and uses parallel finite-state machines together with an event<br>logic to recognize well-for The *Time Map* model of phonological interpretation assumes lattices of acoustic-<br>phonetic events as input and uses parallel finite-state machines together with an event<br>logic to recognize well-formed syllable structures, phonetic events as input and uses parallel finite-state machines together with an event<br>logic to recognize well-formed syllable structures, allowing a distinction to be made<br>between actual (i.e. those in the lexicon) and p logic to recognize well-formed syllable structures, allowing a distinction to be made<br>between actual (i.e. those in the lexicon) and potential forms. The speech signal is rep-<br>resented as tiers of features which are interp between actual (i.e. those in the lexicon) and potential forms. The speech signal is rep-<br>resented as tiers of features which are interpreted in terms of overlap and precedence<br>relations between events, avoiding a rigid se resented as tiers of features which are interpreted in terms of overlap and precedence<br>
relations between events, avoiding a rigid segmentation into non-overlapping units<br>
and allowing coarticulation variants to be modelle relations between events, avoiding a rigid segmentation into non-overlapping units and allowing coarticulation variants to be modelled. The constraint-based *Time Map* model of phonological interpretation has been implemented and evaluated within a linguistic speech-recognition system that uses an increm model of phonological interpretation has b<br>linguistic speech-recognition system that u<br>Berndsen (1998) provides further details.<br>This paper will first introduce the finiteguistic speech-recognition system that uses an incremental architecture. Carson-<br>erndsen (1998) provides further details.<br>This paper will first introduce the finite-state methodology and motivate the use<br>multilinear repres

Berndsen (1998) provides further details.<br>This paper will first introduce the finite-state methodology and motivate the use<br>of multilinear representations of phonological structures in the context of speech<br>recognition. Th This paper will first introduce the finite-state methodology and motivate the use<br>of multilinear representations of phonological structures in the context of speech<br>recognition. The temporal interpretation of these struct of multilinear representations of phonological structures in the context of speech<br>recognition. The temporal interpretation of these structures with respect to an event<br>logic will then be presented and the *Time Map* model recognition. The temporal interpretation of these structures with respect to an event<br>logic will then be presented and the  $Time\ Map$  model will be discussed in the context<br>of a linguistic speech-recognition system. Finally, t

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model that lend themselves to the incorporation of statistical data will be highlighted<br>in the context of the overall architecture. in the context of the overall architecture.

# 2. Finite-state models

2. Finite-state models<br>Finite-state techniques have been used extensively in both computational phonol-<br>ogy and speech recognition. However, it would be fair to say that much of the Finite-state techniques have been used extensively in both computational phonology and speech recognition. However, it would be fair to say that much of the research into finite-state techniques in phonology has not concen Finite-state techniques have been used extensively in both computational phonology and speech recognition. However, it would be fair to say that much of the research into finite-state techniques in phonology has not concen ogy and speech recognition. However, it would be fair to say that much of the research into finite-state techniques in phonology has not concentrated particularly on speech-technology applications, and, conversely, statist research into finite-state techniques in phonology has not concentrated particularly<br>on speech-technology applications, and, conversely, statistical finite-state models,<br>such as hidden Markov models, have not, in the major on speech-technology applications, and, conversely, statistical finite-state models, such as hidden Markov models, have not, in the majority of cases, made explicit use of phonological constraints. This section will conce such as hidden Markov models, have not, in the majority of cases, made explicit<br>use of phonological constraints. This section will concentrate on those aspects of<br>finite-state phonology that are relevant to the *Time Map* use of phonological constraints. This section will conc<br>finite-state phonology that are relevant to the *Time Ma*<br>information can be found in Carson-Berndsen (1998).<br>Finite-state phonology distinguishes between linear ite-state phonology that are relevant to the *Time Map* model; further background<br>formation can be found in Carson-Berndsen (1998).<br>Finite-state phonology distinguishes between linear and multilinear representa-<br>ons. Linea

information can be found in Carson-Berndsen (1998).<br>Finite-state phonology distinguishes between linear and multilinear representa-<br>tions. Linear finite-state phonology—exhibited in the work of Koskenniemi (1983),<br>Kaplan Finite-state phonology distinguishes between linear and multilinear representations. Linear finite-state phonology—exhibited in the work of Koskenniemi (1983), Kaplan & Kay (1994) and others—has been very influential in t tions. Linear finite-state phonology—exhibited in the work of Koskenniemi (1983),<br>Kaplan & Kay (1994) and others—has been very influential in the area of computa-<br>tional linguistics in general, and the methodology has been Kaplan & Kay (1994) and others—has been very influential in the area of computational linguistics in general, and the methodology has been used in a wide application area covering morphological analysers, spellers, hyphen tional linguistics in general, and the methodology has been used in a wide application<br>area covering morphological analysers, spellers, hyphenators, part-of-speech tagging,<br>indexing, and retrieval (see the Web pages of Xer area covering morphological analysers, spellers, hyphenators, part-of-speech tagging,  $\frac{1}{2}$  indexing, and retrieval (see the Web pages of Xerox Research and Lingsoft†). Multilinear finite-state phonology has dealt wit indexing, and retrieval (see the Web pages of Xerox Research and Lingsoft†). Multilinear finite-state phonology has dealt with the formalization and implementation<br>of nonlinear models such as autosegmental phonology and n tilinear finite-state phonology has dealt with the formalization and implementation<br>of nonlinear models such as autosegmental phonology and non-concatenative mor-<br>phology by Kay (1987), Bird & Ellison (1994), Kornai (1995) of nonlinear models such as autosegmental phonology and non-concatenative morphology by Kay (1987), Bird & Ellison (1994), Kornai (1995) and others. The *Time Map* approach is concerned with multilinear finite-state phonol phology by Kay (1987), Bird & Ellison (1994), Kornai (1995) and others. The  $Time$ *Map* approach is concerned with multilinear finite-state phonology. It differs from the above, however, in that it aims to provide a complete set of constraints on syllable structures and in that it has been integrated i the above, however, in that it aims to provide a complete set of constraints on syllable structures and in that it has been integrated into an actual speech-recognition application for German.<br>Constraints on phonological w Lable structures and in that it has been integrated into an actual speech-recognition

application for German.<br>Constraints on phonological well-formedness can be represented declaratively in<br>terms of networks which can be interpreted by finite-state automata. Such con-<br>straints, known as phonotactics, repres Constraints on phonological well-formedness can be represented declaratively in<br>terms of networks which can be interpreted by finite-state automata. Such con-<br>straints, known as phonotactics, represent the possible combina terms of networks which can be interpreted by finite-state automata. Such constraints, known as phonotactics, represent the possible combinations of sounds of a language within a particular phonological domain, usually the **'HYSICAL''''''''''''''**<br>'' ENGINEERING<br>'CIENCES straints, known as phonotactics, represent the possible combinations of sounds of a language within a particular phonological domain, usually the syllable. An example of such an automaton representation, of CCV- combinatio ple of such an automaton representation, of CCV- combinations in German syllable<br>onsets, is depicted in the network of figure 1. The *Time Map* model extends this sim-<br>ple linear model of phonotactic constraints to a multi onsets, is depicted in the network of figure 1. The *Time Map* model extends this simonsets, is depicted in the network of figure 1. The *Time Map* model extends this sim-<br>ple linear model of phonotactic constraints to a multilinear model where labels on<br>the arcs of the automaton representation are no lon ple linear model of phonotactic constraints to a multilinear model where labels on<br>the arcs of the automaton representation are no longer simple phonemes, but, rather,<br>represent constraints on temporal overlap relations wh the arcs of the automaton representation are no longer simple phonemes, but, rather, represent constraints on temporal overlap relations which occur in each structural position. Examples of such constraints for two transit represent constraints on temporal overlap relations which occur in each structural<br>position. Examples of such constraints for two transitions are shown in the figure.<br>The arcs specify only those constraints required in the position. Examples of such constraints for two transitions are shown in the figure.<br>The arcs specify only those constraints required in the particular structural position,<br>i.e. they are based on natural classes of features The arcs specify only those constraints required in the particular structure i.e. they are based on natural classes of features and are, in general, un with respect to all the features needed to define any individual sound The advantage of natural classes of features and are, in general, underspecified<br>th respect to all the features needed to define any individual sound.<br>The advantage of this type of representation of phonotactic constraints

with respect to all the features needed to define any individual sound.<br>The advantage of this type of representation of phonotactic constraints is that an<br>interpretation of multilinear phonological representations, as foun The advantage of this type of representation of phonotactic constraints is that an interpretation of multilinear phonological representations, as found in autosegmental and articulatory phonology, is made possible. Figure interpretation of multilinear phonological representations, as found in autosegmental<br>and articulatory phonology, is made possible. Figure 2 shows a multilinear represen-<br>tation of the potential word *blant* including coar and articulatory phonology, is made possible. Figure 2 shows a multilinear representation of the potential word *blant* including coarticulation. It consists of a set of parallel tiers of features, each of which has its ow tation of the potential word *blant* including coarticulation. It consists of a set of parallel tiers of features, each of which has its own temporal pattern or melody. Only three phonological tiers are shown for the purpo parallel tiers of features, each of which has its own temporal pattern or melody. Only three phonological tiers are shown for the purposes of illustration. Each tier has its own segmentation and the startpoints and endpoints of each of the features on the tiers may differ, which makes the multilinear represe Fig. 21 or  $\mu$  Xerox: [http://www.xrce.xerox.com/research/mltt/fst/;](http://www.xrce.xerox.com/research/mltt/fst/%3B) Lingsoft: http://www.lingsoft.fi/.

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Figure 1. An automaton representation of German CCV- combinations.



Figure 2. A multilinear representation of the potential word *blant*.<br>from a standard segmental phonological representation in which all the features are<br>subject to the same segmentation from a standard segmental phonology<br>subject to the same segmentation.<br>The phonotactic automaton define Im a standard segmental phonological representation in which all the features are<br>bject to the same segmentation.<br>The phonotactic automaton defines a structured set of constraints which repre-<br>nts a complete phonotactics o

subject to the same segmentation.<br>The phonotactic automaton defines a structured set of constraints which represents a complete phonotactics of a language and can distinguish between well-formed<br>and ill-formed structures i The phonotactic automaton defines a structured set of constraints which represents a complete phonotactics of a language and can distinguish between well-formed and ill-formed structures independent of any particular corpu sents a complete phonotactics of a language and can distinguish between well-formed<br>and ill-formed structures independent of any particular corpus and, indeed, of any<br>particular speaker. The temporal constraints of the pho and ill-formed structures independent of any particular corpus and, indeed, of any<br>particular speaker. The temporal constraints of the phonotactics do not assume that<br>a strict segmentation into non-overlapping units has ta It a strict segmentation into non-overlapping units has taken place and, therefore, coar-<br>Iticulation phenomena and many speech variants can be modelled in the multilinear representation.

# 3. Event logics

The *Time Map* model proposes a flexible non-segmental approach to speech recogni-The *Time Map* model proposes a flexible non-segmental approach to speech recognition, which incorporates the notion of compositionality by employing several sources of information simultaneously. Such an approach avoids The *Time Map* model proposes a flexible non-segmental approach to speech recognition, which incorporates the notion of compositionality by employing several sources of information simultaneously. Such an approach avoids a tion, which incorporates the notion of compositionality by employing several sources<br>of information simultaneously. Such an approach avoids a strict segmentation of the<br>speech signal into phonemes or other units of similar of information simultaneously. Such an approach avoids a strict segmentation of the speech signal into phonemes or other units of similar granularity, and, therefore, the acoustic front-end does not have to classify over p speech signal into phonemes or other units of similar granularity, and, therefore, the

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analogous to the multilinear representation depicted in figure 2, except, of course, analogous to the multilinear representation depicted in figure 2, except, of course, that it consists of more than three tiers. This representation of acoustic information in a multilinear structure of sequential and para analogous to the multilinear representation depicted in figure 2, except, of course, that it consists of more than three tiers. This representation of acoustic information in a multilinear structure of sequential and paral that it consists of more than three tiers. This representation of acoustic information<br>in a multilinear structure of sequential and parallel features is nearer to the sig-<br>nal than the phoneme sequences of more traditional in a multilinear structure of sequential and parallel features is nearer to the signal than the phoneme sequences of more traditional phonologies. In order to relate the features in such a representation both to the speec

nal than the phoneme sequences of more traditional phonologies. In order to relate<br>the features in such a representation both to the speech signal and to the temporal<br>constraints specified in the phonotactic automaton, the the features in such a representation both to the speech signal and to the temporal constraints specified in the phonotactic automaton, the *Time Map* model uses an event logic based on time-type domains which coexist as constraints specified in the phonotactic automaton, the *Time Map* model uses an event logic based on time-type domains which coexist as different perspectives on spoken-language utterances (see Gibbon 1992). The *Time Ma* event logic based on time-type domains which coexist as different perspectives on spoken-language utterances (see Gibbon 1992). The *Time Map* model is primarily concerned with a *relative-time domain*  $(T_{rel})$ , which is an spoken-language utterances (see Gibbon 1992). The *Time Map* model is primarily concerned with a *relative-time domain*  $(T_{rel})$ , which is an abstract temporal domain in which categories are assumed to have duration and can concerned with a *relative-time domain*  $(T_{rel})$ , which is an abstract temporal domain<br>in which categories are assumed to have duration and can be viewed as intervals<br>with temporal relations between them, and an *absolute-t* in which categories are assumed to have duration and can be viewed as intervals<br>with temporal relations between them, and an *absolute-time domain*  $(T_{\text{abs}})$ , which<br>is an utterance time domain in which categories have a with temporal relations between them, and an *a* is an utterance time domain in which categories<br>therefore, a direct reference to real signal time.<br>The problem of representing temporal knowled an utterance time domain in which categories have a temporal annotation and,<br>erefore, a direct reference to real signal time.<br>The problem of representing temporal knowledge and of temporal reasoning with<br>is knowledge has b

therefore, a direct reference to real signal time.<br>The problem of representing temporal knowledge and of temporal reasoning with<br>this knowledge has been investigated by Allen (1983), Van Benthem (1983) and<br>Freksa (1992), a The problem of representing temporal knowledge and of temporal reasoning with<br>this knowledge has been investigated by Allen (1983), Van Benthem (1983) and<br>Freksa (1992), among others. Building on this work, proposals have this knowledge has been investigated by Allen (1983), Van Benthem (1983) and Freksa (1992), among others. Building on this work, proposals have been made in computational phonology for providing multilinear phonological r Freksa (1992), among others. Building on this work, proposals have been made in<br>computational phonology for providing multilinear phonological representations with<br>a formal interpretation using events and the axioms of eve computational phonology for providing multilinear phonological representations with<br>a formal interpretation using events and the axioms of event logic (Bird & Klein 1990;<br>Carson-Berndsen 1998), such that feature co-occurre a formal interpretation using events and the axioms of event logic (Bird & Klein 1990;<br>
Carson-Berndsen 1998), such that feature co-occurrence (or association in autoseg-<br>
[mental phonology terms) is interpreted as tempor poral precedence. Although such an approach allows the explicit introduction of a mental phonology terms) is interpreted as temporal overlap and sequencing as tem-<br>poral precedence. Although such an approach allows the explicit introduction of a<br>temporal dimension into the phonological description, a r poral precedence. Although such an approach allows the explicit introduction of a<br>temporal dimension into the phonological description, a restriction of this interpre-<br>tation to  $T_{rel}$ , as proposed by Bird (1995), has the temporal dimension into the phonological description, a restriction of this interpre-<br>tation to  $T_{rel}$ , as proposed by Bird (1995), has the consequence that no reference can<br>be made to actual speech tokens with absolute-t tation to  $T_{rel}$ , as proposed by Bird (1995), has the consequence that no reference can<br>be made to actual speech tokens with absolute-time annotations. Speech recogni-<br>tion, however, requires a mapping from absolute-time be made to actual speech tokens with absolute-time annotations. Speech recognition, however, requires a mapping from absolute-time annotations to a relative-time domain in which actual time is no longer needed ( $T_{abs} \rightarrow T_{rel$ tion, however, requires a mapping from absolute-time annotations to a relative-time<br>domain in which actual time is no longer needed  $(T_{\text{abs}} \rightarrow T_{\text{rel}})$ .<br>The *Time Map* model distinguishes between events in  $T_{\text{rel}}$  and e

**A relative-time event** is defined as an ordered pair  $\rho \tau \epsilon = \langle I, F \rangle$ , where *I* refers to some interval in the time domain  $T_{rel}$  and *F* refers to a feature or property of the interval. to some interval in the time domain  $T_{rel}$  and F refers to a feature or property of

**IATHEMATICAL,<br>HYSICAL<br>< ENGINEERING<br>CIENCES** For example, in the multilinear representation in figure 2, the feature *voiced* on the phonation tier can be a relative-time event  $\rho \tau \epsilon_1 = \langle I_1, \text{voiced}_{\text{phonation}} \rangle$ .<br>**An absolute-time event** is defined as an ordered pair For example, in the multilinear representation in figure 2, the feature *voiced* on the phonation tier can be a relative-time event  $\rho \tau \epsilon_1 = \langle I_1$ , voiced<sub>phonation</sub>).

is the starting time of the interval and  $t_f$  is the finishing time of the interval in<br>the time domain  $T_{\text{abs}}$ . F is the feature or property of the interval bounded by  $t_s$ An absolute-time event is defined as an ordered pair  $\alpha \tau \epsilon = \langle \langle t_s, t_f \rangle, F \rangle$ , where  $t_s$  is the starting time of the interval and  $t_f$ .<br>the time domain  $T_{\text{abs}}$ . F is the feature or property of the interval bounded by

**be a** absolute-time domain, the feature *voiced* of figure 2 can <br>be an absolute-time event  $\alpha \tau \epsilon_1 = \langle \langle 113, 432 \rangle$ , voiced<sub>phonation</sub>).<br>Relative-time events and absolute-time events are governed by systems of axioms,

be an absolute-time event  $\alpha \tau \epsilon_1 = \langle \langle 113, 432 \rangle$ , voiced<sub>phonation</sub>).<br>Relative-time events and absolute-time events are governed by systems of axioms,<br>and the basic rule of inference is *modus ponens*. The complete ax Relative-time events and absolute-time events are governed by systems of axioms,<br>and the basic rule of inference is *modus ponens*. The complete axiom set is given in<br>Carson-Berndsen (1998, 73ff); a subset for each event t and the basic rule of inference is *modus ponens*. The complete axiom set is given in Carson-Berndsen (1998, 73ff); a subset for each event type is given below for illustration. There are seven axioms governing the tempor Carson-Berndsen (1998, 73ff); a subset for each event type is given below for illustra-<br> **O** tion. There are seven axioms governing the temporal relations between relative-time events. Those governing overlap ( $\circ$ ) and precedence ( $\prec$ ) are

R1 : 
$$
\rho\tau\epsilon_i \circ \rho\tau\epsilon_i
$$
,  
\nR2 :  $\rho\tau\epsilon_i \circ \rho\tau\epsilon_j \rightarrow \rho\tau\epsilon_j \circ \rho\tau\epsilon_i$ ,  
\nR3 :  $\rho\tau\epsilon_i \prec \rho\tau\epsilon_j \rightarrow \neg \rho\tau\epsilon_j \prec \rho\tau\epsilon_i$ .

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 $1260$   $J. ~Carson-Berndsen$ <br>There are 14 axioms governing the relations of temporal inclusion, overlap and prece-NEERING There are 14 axioms governing the relations of temporal inclusion, overlap and precedence between absolute-time events. Examples of an axiom governing overlap and an axiom governing precedence of two absolute-time events, dence between absolute-time events. Examples of an axiom governing overlap and an ce between absolute-time events. Examples of an axiom governing precedence of two absolute-time events,  $\alpha \tau \epsilon$ <br>  $\alpha_2 = \langle \langle t_{s2}, t_{f2} \rangle, F_2 \rangle$ , are given in *A3* and *A5*, respectively:  $\alpha \tau \epsilon_2 = \langle \langle t_{s2}, t_{f2} \rangle, F_2 \rangle$ , are given in A3 and A5, respectively:

$$
A3: t_{s1} \leq t_{s2} \wedge t_{f1} \geq t_{s2} \rightarrow \alpha \tau \epsilon_1 \circ \alpha \tau \epsilon_2
$$
  

$$
A5: t_{f1} < t_{s2} \rightarrow \alpha \tau \epsilon_1 \prec \alpha \tau \epsilon_2.
$$

Applying these axioms in the time domain  $T_{\text{abs}}$  to the events in the multilinear Applying these axioms in the time domain  $T_{\text{abs}}$  to the events in the multilinear<br>representation of figure 2, for example, would allow the inference to be made that<br>the event with the feature *voiced* overlaps (o) the e Applying these axioms in the time domain  $T_{\text{abs}}$  to the events in the multilinear representation of figure 2, for example, would allow the inference to be made that the event with the feature *voiceless*. ( $\leq$ ) the ev  $\Box$  the event with the feature *voiced* overlaps ( $\circ$ ) the event with the feature *plosive*,<br>and precedes ( $\prec$ ) the event with the feature *voiceless*. There is a close relationship<br>between absolute-time events and rel between absolute-time events and relative-time events; the latter is an abstraction between absolute-time events and relative-time events; the latter is an abstraction<br>of the former, that is to say, it represents the same facts but in a different tempo-<br>ral domain. Although the relative-time domain and th of the former, that is to say, it represents the same facts but in a different temporal domain. Although the relative-time domain and the absolute-time domain are conceptually separate, they can be conflated for the purpos % conceptually separate, they can be conflated for the purposes of implementation.<br>4. Finite-state models and event logics in speech recognition

The finite-state model and the event logic together form the basis for a constraint-The finite-state model and the event logic together form the basis for a constraint-<br>based approach to phonological parsing based on the temporal interpretation of<br>phonological categories as events, and using a flexible no The finite-state model and the event logic together form the basis for a constraint-<br>based approach to phonological parsing based on the temporal interpretation of<br>phonological categories as events, and using a flexible no phonological categories as events, and using a flexible notion of compositionality based on underspecified structures with autosegmental tiers of parallel phonetic and phonological categories as events, and using a flexible notion of compositionality<br>based on underspecified structures with autosegmental tiers of parallel phonetic and<br>phonological events. The overall architecture of the based on underspecified structures with autosegmental<br>phonological events. The overall architecture of the  $Ti$ <br>of linguistic word recognition is depicted in figure 3.<br>The autonomous feature-extraction component and conological events. The overall architecture of the *Time Map* model in the context<br>linguistic word recognition is depicted in figure 3.<br>The autonomous feature-extraction component and the word parser provide the<br>serfaces

of linguistic word recognition is depicted in figure 3.<br>The autonomous feature-extraction component and the word parser provide the<br>interfaces to the model. Features are detected individually from the speech signal<br>by an a The autonomous feature-extraction component and the word parser provide the<br>interfaces to the model. Features are detected individually from the speech signal<br>by an autonomous feature-extraction component, which serves as interfaces to the model. Features are detected individually from the speech signal<br>by an autonomous feature-extraction component, which serves as a front-end to the<br>phonological parser. The feature-extraction component doe by an autonomous feature-extraction component, which serves as a front-end to the phonological parser. The feature-extraction component does not classify over phones or phonemes but rather treats each feature as autonomous phonological parser. The feature-extraction component does not classify over phones

**IATHEMATICAL,<br>HYSICAL<br>< ENGINEERING<br>CIENCES** or phonemes but rather treats each feature as autonomous.<br>The features detected by the feature-extraction component are output together<br>with their temporal annotations or boundary points and are represented in the fig-<br>ure The features detected by the feature-extraction component are output together<br>with their temporal annotations or boundary points and are represented in the fig-<br>ure in terms of parallel tiers of autonomous features; for il with their temporal annotations or boundary points and are represented in the figure in terms of parallel tiers of autonomous features; for illustrative purposes, only three tiers are shown. Each tier in this linear repres ure in terms of parallel tiers of autonomous features; for illustrative purposes, only<br>three tiers are shown. Each tier in this linear representation has its own temporal<br>pattern or melody, and, therefore, the segmentation three tiers are shown. Each tier in this linear representation has its own temporal pattern or melody, and, therefore, the segmentation function across tiers is not the same as would be assumed by segmental phonologies. R pattern or melody, and, therefore, the segmentation function across tiers is not the same as would be assumed by segmental phonologies. Rather than performing a segmentation into connected chart nodes, the *Time Map* solut same as would be assumed by segmental phonologies. Rather than performing a<br>segmentation into connected chart nodes, the *Time Map* solution to the *lattice-to-*<br>*chart* problem is based on a mapping from the temporal anno segmentation into connected chart nodes, the *Time Map* solution to the *lattice-to-*<br>*chart* problem is based on a mapping from the temporal annotations or boundary<br>points to temporal relations between the hypotheses usin then carried out entirely using the relations rather than the temporal annotations. then carried out entirely using the relations rather than the temporal annotations.<br>Gaps are interpreted in terms of immediate precedence relations and overlapping<br>properties are interpreted in terms of overlap relations. Gaps are interpreted in terms of immediate precedence relations and overlapping Gaps are interpreted in<br>properties are interpreted<br>incremental processing.<br>As was discussed in the operties are interpreted in terms of overlap relations. This approach is suitable for<br>cremental processing.<br>As was discussed in the section on finite-state models, the phonotactic automaton<br>the phonological parser provides

 $\sum_{n=1}^{\infty}$  as was discussed in the section on finite-state models, the phonotactic automaton<br>of the phonological parser provides top-down constraints on the interpretation of the As was discussed in the section on finite-state models, the phonotactic automaton<br>of the phonological parser provides top-down constraints on the interpretation of the<br>multilinear representations, specifying which overlap of the phonological parser provides top-down constraints on the interpretation of the multilinear representations, specifying which overlap and precedence relations are expected by the phonotactics. Each time a final state multilinear representations, specifying which overlap and precedence relations are<br>expected by the phonotactics. Each time a final state of the automaton is reached,<br>a well-formed syllable structure has been found. Since t expected by the phonotactics. Each time a final state of the automaton is reached, a well-formed syllable structure has been found. Since the input to the phonological parser is, in general, assumed to be underspecified du

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rigure 3. The *Time map* moder in the context of inguistic speech recognition.<br>must provide means of minimizing the discrepancy between the expectations defined<br>in the top-down constraints and the actual data by allowing c must provide means of minimizing the discrepancy between the expectations defined<br>in the top-down constraints and the actual data by allowing constraint relaxation and<br>constraint enhancement. Constraint relaxation should b must provide means of minimizing the discrepancy between the expectations defined in the top-down constraints and the actual data by allowing constraint relaxation and dependent if only some of the constraints specified by in the top-down constraints and the actual data by allowing constraint relaxation and<br>constraint enhancement. Constraint relaxation should be performed if only some of<br>the constraints specified by the phonotactic automaton constraint enhancement. Constraint relaxation should be performed if only some of<br>the constraints specified by the phonotactic automaton can be satisfied. Constraint<br>enhancement should be performed to further specify the o enhancement should be performed to further specify the output if the constraints specify expectations that do not conflict with information found in the input. Clearly,

enhancement should be performed to further specify the output if the constraints<br>specify expectations that do not conflict with information found in the input. Clearly,<br>constraint relaxation and constraint enhancement are specify expectations that do not conflict with information found in the input. Clearly,<br>constraint relaxation and constraint enhancement are interdependent and require a<br>ranking of the constraints. This point will be discu constraint relaxation and constraint enhancement are interdependent and require a<br>ranking of the constraints. This point will be discussed further in the next section. It<br>is important to note, however, that the application ranking of the constraints. This point will be discussed further in the next section. It<br>is important to note, however, that the application of constraint enhancement does<br>not guarantee that the output syllable structures is important to no<br>not guarantee tha<br>are well-formed.<br>Coarticulation i t guarantee that the output syllable structures are fully specified, only that they<br>e well-formed.<br>Coarticulation is modelled by overlap of information in the multilinear represen-<br>tions. Since the overlap relations specif

are well-formed.<br>Coarticulation is modelled by overlap of information in the multilinear representations. Since the overlap relations specified in the phonotactic constraints do not require features on different tiers to b Coarticulation is modelled by overlap of information in the multilinear representations. Since the overlap relations specified in the phonotactic constraints do not require features on different tiers to begin and end at t tations. Since the overlap relations specified in the phonotactic constraints do not<br>require features on different tiers to begin and end at the same time, a strict seg-<br>mentation into non-overlapping units is not necessar require features on different tiers to begin and end at the same time, a strict seg-<br>mentation into non-overlapping units is not necessary. Phonological phenomena such<br>as assimilations and elisions can, therefore, be repre as assimilations and elisions can, therefore, be represented in line with articulatory phonology in terms of feature (or gestural) overlap and magnitude. The degrees of as assimilations and elisions can, therefore, be represented in line with articulate<br>phonology in terms of feature (or gestural) overlap and magnitude. The degrees<br>overlap and magnitude are relevant for constraint relaxati onology in terms of feature (or gestural) overlap and magnitude. The degrees of<br>erlap and magnitude are relevant for constraint relaxation and enhancement.<br>The phonological parser outputs well-formed syllable structures wh

overlap and magnitude are relevant for constraint relaxation and enhancement.<br>The phonological parser outputs well-formed syllable structures which are then<br>input to a corpus lexicon. The corpus lexicon acts as a filter di The phonological parser outputs well-formed syllable structures which are then<br>input to a corpus lexicon. The corpus lexicon acts as a filter distinguishing between<br>actual and potential syllables by assigning a higher conf *Phil. Trans. R. Soc. Lond.* A (2000)

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 $1262$   $J. ~Carson-Berndsen$ <br>bles of the corpus. These ranked syllable hypotheses are then passed, together with<br>their temporal annotations, to the word parser. Since the syllable structures may be bles of the corpus. These ranked syllable hypotheses are then passed, together with<br>their temporal annotations, to the word parser. Since the syllable structures may be<br>underspecified, the lexicon is feature based and, the bles of the corpus. These ranked syllable hypotheses are then passed, together with<br>their temporal annotations, to the word parser. Since the syllable structures may be<br>underspecified, the lexicon is feature based and, the their temporal annotations, to the word parser. Since the syllable structures may be underspecified, the lexicon is feature based and, therefore, full specifications can be provided for corpus syllables if required. Howeve underspecified, the lexicon is feature based and, therefore, full specifications can be provided for corpus syllables if required. However, fully specified structures are not assumed by the word parser, since the main aim provided for corpus syllables if required. However, fully specified assumed by the word parser, since the main aim of this approa full specification in order to reduce the number of hypotheses.<br>The *Time Man* model has bee

sumed by the word parser, since the main aim of this approach is to postpone a<br>Il specification in order to reduce the number of hypotheses.<br>The *Time Map* model has been implemented and tested within a linguistic word-<br>co full specification in order to reduce the number of hypotheses.<br>The *Time Map* model has been implemented and tested within a linguistic word-<br>recognition system, which is part of an experimental development environment f The *Time Map* model has been implemented and tested within a linguistic word-<br>recognition system, which is part of an experimental development environment for<br>speech-recognition architectures. Within this system, the comp speech-recognition architectures. Within this system, the components can demon-<br>strate differing interaction strategies and parameter settings for different types of speech-recognition architectures. Within this system, the components can demonstrate differing interaction strategies and parameter settings for different types of analysis. Although performance was not the main concern of strate differing interaction strategies and parameter settings for different types of analysis. Although performance was not the main concern of this work, a diagnostic evaluation has been performed with varying parametriz analysis. Although performance was not the main concern of this work, a diagnostic<br>evaluation has been performed with varying parametrizations of the system, which<br>has led to some very promising results. As was mentioned a evaluation has been performed with varying parametrizations of the system, which<br>has led to some very promising results. As was mentioned above, the well-formed<br>structures recognized at each level are in general underspeci has led to some very promising results. As was mentioned above, the well-formed<br>structures recognized at each level are in general underspecified, but full specifica-<br>tions in terms of phonemes or syllables can be calculat structures recognized at each level are in general underspecified, but full specifications in terms of phonemes or syllables can be calculated for evaluation. However, since this approach explicitly avoids a segmentation o tions in terms of phonemes or syllables can be calculated for evaluation. However, since this approach explicitly avoids a segmentation of the speech signal into non-overlapping units, a standard string-alignment evaluatio since this approach explicitly avoids a segmer<br>overlapping units, a standard string-alignment<br>for assessing the performance of the system.<br>A diagnostic evaluation procedure for the erlapping units, a standard string-alignment evaluation procedure was not suitable<br>  $\Lambda$  diagnostic evaluation procedure for the *Time Map* model was developed that<br>
nsisted of a logical evaluation with respect to a data m

for assessing the performance of the system.<br>A diagnostic evaluation procedure for the *Time Map* model was developed that<br>consisted of a logical evaluation, with respect to a data model, and an empirical  $\overline{\delta}$ A diagnostic evaluation procedure for the *Time Map* model was developed that consisted of a logical evaluation, with respect to a data model, and an empirical evaluation, with respect to real signal data. The logical eva consisted of a logical evaluation, with respect to a data model, and an empirical<br>evaluation, with respect to real signal data. The logical evaluation was responsible<br>for testing the soundness and completeness of the parse evaluation, with respect to real signal data. The logical evaluation was responsible<br>for testing the soundness and completeness of the parser and knowledge components<br>of the model with fully specified data, and the empiric for testing the soundness and completeness of the parser and knowledge components<br>of the model with fully specified data, and the empirical evaluation tested the per-<br>formance of the model in the context of the complete w of the model with fully specified data, and the empirical evaluation tested the per-<br>formance of the model in the context of the complete word-recognition system. In<br>addition to a string-alignment evaluation, a *Time Map* formance of the model in the context of the complete word-recognition system. In addition to a string-alignment evaluation, a *Time Map* evaluation procedure was performed. With one particular parametrization of the syste addition to a string-alignment evaluation, a *Time Map* evaluation procedure was<br>performed. With one particular parametrization of the system, a phoneme recog-<br>nition rate of 66.97% and a syllable recognition rate of 35.1 performed. With one particular parametrization of the system, a phoneme recognition rate of 66.97% and a syllable recognition rate of 35.19% were attained on many-speaker utterances of spontaneous scheduling task dialogues nition rate of 66.97% and a syllable recognition rate of 35.19% were attained on<br>many-speaker utterances of spontaneous scheduling task dialogues. Diagnostic eval-<br>uation showed that the relatively low syllable-recognition **MATHEMATICAL,<br>PHYSICAL<br>& ENGINEERING<br>SCIENCES** many-speaker utterances of spontaneous scheduling task dialogues. Diagnostic evaluation showed that the relatively low syllable-recognition rate was due to one or two features being unreliable, leading to the complete syll uation showed that the relatively low syllable-recognition rate was due to one or two<br>features being unreliable, leading to the complete syllable not being recognized. Fur-<br>thermore, since phoneme recognition was not a tas thermore, since phoneme recognition was not a task of the phonological parser, the phoneme rate was calculated on the basis of the recognized syllables. However, the results are remarkable for a purely knowledge-based syst thermore, since phoneme recognition was not a task of the phonological parser, the phoneme rate was calculated on the basis of the recognized syllables. However, the results are remarkable for a purely knowledge-based system and it is anticipated that improvements will be made by more efficient constrain results are remarkable for a purely knowledge-based system and it is anticipated that<br>improvements will be made by more efficient constraint-relaxation and constraint-<br>enhancement procedures, as will be discussed in the ne improvements will be made by more efficient constraint-relaxation and constraint-<br>enhancement procedures, as will be discussed in the next section. Further details of<br>the evaluation procedure and the results can be found i

# 5. Integrating statistics

5. Integrating statistics<br>The *Time Map* model is a formally specified linguistic-symbolic approach with fine<br>granularity which offers a solution to the problem of projecting onto potentially The *Time Map* model is a formally specified linguistic-symbolic approach with fine<br>granularity which offers a solution to the problem of projecting onto potentially<br>well-formed structures at the phonetics-phonology inter The *Time Map* model is a formally specified linguistic-symbolic approach with fine<br>granularity which offers a solution to the problem of projecting onto potentially<br>well-formed structures at the phonology interface in spe granularity which offers a solution to the problem of projecting onto potentially<br>well-formed structures at the phonetics-phonology interface in speech recognition.<br>However, in the same way that the fine-grained knowledge well-formed structures at the phonetics-phonology interface in speech recognition.<br>However, in the same way that the fine-grained knowledge of this model has been<br>used to fine-tune stochastic models with considerable succ However, in the same way that the fine-grained knowledge of this model has been<br>used to fine-tune stochastic models with considerable success, so it is also possible<br>to use statistical information to fine-tune the *Time Ma* used to fine-tune stochastic models with considerable success, so it is also possible<br>to use statistical information to fine-tune the *Time Map* approach for specific appli-<br>cations. The rest of this paper identifies the to use statistical information to fine-tune the *Time Map* approach for specific applications. The rest of this paper identifies the areas in which statistics can play a role and discusses these with respect to the overal cations. The rest of this paper identifies the areas in which statistics can play a role and discusses these with respect to the overall architecture. There are three main integration areas for statistics in the *Time Map* integration areas for statistics in the *Time Map* model which differ in granularity.<br>*Phil. Trans. R. Soc. Lond.* A (2000)

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Finite-state models, event logics and statistics 1263<br>The first integration area is constraint ranking, which represents the lowest level of<br>granularity in that the constraints refer to individual temporal relations. The s The first integration area is constraint ranking, which represents the lowest level of granularity in that the constraints refer to individual temporal relations. The second area of integration is in connection with the we granularity in that the constraints refer to individual temporal relations. The second area of integration is in connection with the weighting of the phonotactic automaton. Automaton weighting is a higher level of granularity in that the whole transition is area of integration is in connection with the weighting of the phonotactic automaton.<br>Automaton weighting is a higher level of granularity in that the whole transition is<br>weighted rather than individual constraints. The th Automaton weighting is a higher level of granularity in that the whole transition is<br>weighted rather than individual constraints. The third integration area for statistic<br>is the lexicon that refers to a yet higher level of

exighted rather than individual constraints. The third integration area for statistics<br>the lexicon that refers to a yet higher level of granularity, namely the syllable.<br>The notion of constraint ranking was seen in the pre is the lexicon that refers to a yet higher level of granularity, namely the syllable.<br>The notion of constraint ranking was seen in the previous section to play an impor-<br>tant role in constraint relaxation and constraint en The notion of constraint ranking was seen in the previous section to play an important role in constraint relaxation and constraint enhancement. Constraint ranking for this model can be based on a number of factors: lingui this model can be based on a number of factors: linguistic-preferential, cognitive and statistical. Linguistic-preferential refers to issues of markedness and defaults, cognithis model can be based on a number of factors: linguistic-preferential, cognitive and statistical. Linguistic-preferential refers to issues of markedness and defaults, cognitive refers to human processing issues, and stat statistical. Linguistic-preferential refers to issues of markedness and defaults, cogni-<br>tive refers to human processing issues, and statistical refers to data-oriented issues.<br>The rest of this section will only be concern tive refers to human processing issues, and statistical refers to data-oriented issues.<br>The rest of this section will only be concerned with such data-oriented ranking,<br>although, clearly, it is more likely that a combinati The rest of this section will only be concerned with such data-oriented ranking,<br>although, clearly, it is more likely that a combination of the factors will be appro-<br>priate for constraint ranking, and, therefore, a free p although, clearly, it is more likely that a combination of the factors will be appro-<br>priate for constraint ranking, and, therefore, a free parametrization of the system<br>should allow adequate parameters to be chosen that d priate for constraint ranking, and, therefore, a free parametrization of the system should allow adequate parameters to be chosen that define a compromise between maximal recognition rates and minimal analysis overhead.

Constraints may be ranked with respect to frequency, duration and percentage overlap of features in specific structural contexts. This information can either be spemaximal recognition rates and minimal analysis overhead.<br>Constraints may be ranked with respect to frequency, duration and percentage<br>overlap of features in specific structural contexts. This information can either be spe-Constraints may be ranked with respect to frequency, duration and percentage<br>overlap of features in specific structural contexts. This information can either be spe-<br>cific to a single corpus or may be based on data from se overlap of features in specific structural contexts. This information can either be specific to a single corpus or may be based on data from several different corpora. Based<br>on this ranking, constraint relaxation can be ap encountered or a single corpus or may be based on data from several different corpora. Based<br>on this ranking, constraint relaxation can be applied when an infrequent feature is<br>encountered or a duration is outside a standa on this ranking, constraint relaxation can be applied when an infrequent feature is encountered or a duration is outside a standard deviation, for example. Constraint enhancement can also be applied according to such a ran enhancement can also be applied according to such a ranking when a frequent feaenhancement can also be applied according to such a ranking when a frequent fea-<br>ture is expected but not present in the input but there is nothing in the input that<br>would exclude it. This method of constraint ranking for ture is expected but not present in the input but there is nothing in the input that<br>would exclude it. This method of constraint ranking for relaxation and enhancement<br>has yet to be integrated into the model, but this is t would exclude it. This method of constraint ranking for relaxation and enhancement<br>has yet to be integrated into the model, but this is the integration area for statistics<br>which could lead to reductions in the error rate. has yet to be integrated into the model, but this is the integration area for statistics<br>which could lead to reductions in the error rate. The other two integration areas<br>for statistics will influence the size of the searc which could lead to reductions in the error rate. The other two integration areas<br>for statistics will influence the size of the search space and the confidence of the<br>hypotheses and, thus, improve accuracy by reducing the r statistics will influence the size of the search space and the confidence of the potheses and, thus, improve accuracy by reducing the number of false positives.<br>The second area of integration of statistics in the *Time M* 

hypotheses and, thus, improve accuracy by reducing the number of false positives.<br>The second area of integration of statistics in the *Time Map* model is in connection with corpus-based fine-tuning of the phonotactic auto **MATHEMATICAL,<br>PHYSICAL<br>& ENGINEERING<br>SCIENCES** The second area of integration of statistics in the *Time Map* model is in connection with corpus-based fine-tuning of the phonotactic automaton. Using corpus-based statistics, weights can be calculated for the individual tion with corpus-based fine-tuning of the phonotactic automaton. Using corpus-based statistics, weights can be calculated for the individual transitions in the automaton, and, in line with proposals made by Pereira  $\&$  R statistics, weights can be calculated for the individual transitions in the automaton,<br>and, in line with proposals made by Pereira & Riley (1996), the total weight can<br>be defined, using commutative semirings as a formal b and, in line with proposals made by Pereira  $\&$  Riley (1996), the total weight can be defined, using commutative semirings as a formal basis, as the extension of the weights of the corresponding paths. In addition to det be defined, using commutative semirings as a formal basis, as the extension of the weights of the corresponding paths. In addition to determinization and minimization, which make the automaton more efficient from a process weights of the corresponding paths. In addition to determinization and minimization, which make the automaton more efficient from a processing viewpoint, it may also be interesting to experiment with specific data-oriented tion, which make the automaton more efficient from a processing viewpoint, it may<br>also be interesting to experiment with specific data-oriented phonotactic models<br>which are generated with respect to particular corpora. For also be interesting to experiment with specific data-oriented phonotactic models<br>which are generated with respect to particular corpora. For example, Belz (1998)<br>presents an approach for the automatic acquisition of finite which are generated with respect to particular corpora. For example, Belz (1998) presents an approach for the automatic acquisition of finite-state models of phonotactic constraints based on genetic algorithms. The compos presents an approach for the automatic acquisition of finite-state models of phono-<br>tactic constraints based on genetic algorithms. The composition of the data-oriented<br>automaton and the *Time Map* automaton would be anoth tactic constraints based on genetic algorithms. The composition of the data-oriented<br>automaton and the *Time Map* automaton would be another method of assigning a<br>corpus-based weighting to the phonotactic automaton. This i Corpus-based weighting to the phonotactic automaton. This is currently being inves-<br>  $\bullet$  if integration for statistics is the lexicon, and this is the component<br>  $\bullet$  $\bullet$  tigated.

of the *Time Map* model that has made the most use of statistical information thus far. Since the lexicon specifies only those syllables that are in the corpus, it has been The third area of integration for statistics is the lexicon, and this is the component<br>of the *Time Map* model that has made the most use of statistical information thus<br>far. Since the lexicon specifies only those syllabl possible to include in that has made the most use of statistical information thus far. Since the lexicon specifies only those syllables that are in the corpus, it has been possible to include in the syllable entries stati far. Since the lexicon specifies only those syllables that are in the corpus, it has been<br>possible to include in the syllable entries statistical information such as frequency,<br>average duration and standard deviation, both possible to include in the syllable entries statistical information such as frequency, average duration and standard deviation, both of the syllable as a whole and of the duration based on the average durations of its indi duration based on the average durations of its individual parts taking context infor-<br>*Phil. Trans. R. Soc. Lond.* A (2000)

<sup>1264</sup> *J.Carson-Berndsen* Downloaded from rsta.royalsocietypublishing.org

ATHEMATICAL

**DYAL** 

**PHILOSOPHICAL**<br>TRANSACTIONS

**IATHEMATICAL,<br>HYSICAL<br>< ENGINEERING** 

Ξ

**PHILOSOPHICAL**<br>TRANSACTIONS

1264 *J. Carson-Berndsen*<br>mation into account. Currently, this is the only place in the *Time Map* model where NEERING mation into account. Currently, this is the only place in the *Time Map* model where a corpus-based ranking is performed by providing actual (corpus) syllables with a higher confidence value than potential syllables, and a corpus-based ranking is performed by providing actual (corpus) syllables with a a corpus-based ranking is performed by providing actual (corpus) syllables with a higher confidence value than potential syllables, and a more fine-grained ranking of hypotheses within the category of actual syllables is p hypotheses within the category of actual syllables is performed by allowing syllable<br>hypotheses with the greatest degree of specification and which most closely match hypotheses within the category of actual syllables is performed by allowing syllable<br>hypotheses with the greatest degree of specification and which most closely match<br>the average durations to be ranked higher than their co hypotheses with the greatest degree of specification and which most closely<br>the average durations to be ranked higher than their counterparts. This appro-<br>currently under development in the context of an ongoing research p Equivalent than their counterparts. This approach is<br>trently under development in the context of an ongoing research project.<br>This section has been concerned with the integration of statistics into the *Time*<br>an model. It

currently under development in the context of an ongoing research project.<br>This section has been concerned with the integration of statistics into the *Time*<br>*Map* model. It has been shown with respect to the overall archi This section has been concerned with the integration of statistics into the *Time*  $Map$  model. It has been shown with respect to the overall architecture of the model that there are a number of areas in which statistics ca *Map* model. It has been shown with respect to the overall architecture of the model that there are a number of areas in which statistics can play a role. In all that has been said here, however, it should be obvious that in the said here, however, it should be obvious that statistical information is regarded  $\Box$  not as a basis for converting the linguistic–symbolic model to a stochastic one but as an aid for application-specific tuning.

### 6. Conclusion

**6. Conclusion**<br>This paper has been concerned with a computational linguistic model of phonolog-<br>ical interpretation which provides a framework in which multilinear parallel event This paper has been concerned with a computational linguistic model of phonological interpretation which provides a framework in which multilinear parallel event representations of speech utterances are temporally interpre This paper has been concerned with a computational linguistic model of phonological interpretation which provides a framework in which multilinear parallel event representations of speech utterances are temporally interpre ical interpretation which provides a framework in which multilinear parallel event<br>representations of speech utterances are temporally interpreted using finite-state<br>machines. Rather than concentrate purely on system perfo Ğ representations of speech utterances are temporally interpreted using finite-state<br>machines. Rather than concentrate purely on system performance and recognition<br>results, the aim of this approach has been to develop a prin machines. Rather than concentrate purely on system performance and recognition<br>results, the aim of this approach has been to develop a principled, formally specified<br>linguistic theory of phonological interpretation which i linguistic theory of phonological interpretation which investigates the role played by symbolic constraints on well-formedness and provides important fine-grained knowllinguistic theory of phonological interpretation which investigates the role played by<br>symbolic constraints on well-formedness and provides important fine-grained knowl-<br>edge representations for speech-technology applicati symbolic constraints on well-formedness and provides important fine-grained knowl-<br>edge representations for speech-technology applications. The informational struc-<br>tures used by this system could on the one hand be enhanc edge representations for speech-technology applications. The informational structures used by this system could on the one hand be enhanced by statistical information for application-specific tuning but also be made availa tures used by this system could on the one hand be enhanced by statistical infor-<br>mation for application-specific tuning but also be made available to other stochastic<br>word-recognition systems for the purposes of structura word-recognition systems for the purposes of structural fine-tuning. This approach is directly relevant to multi-sensor input applications (see Carson-Berndsen 1999 $a, b$ ), word-recognition systems for the purposes of structural fine-tuning. This approach is<br>directly relevant to multi-sensor input applications (see Carson-Berndsen 1999 $a, b$ ),<br>since the finite-state methodology and the event directly relevant to multi-sensor input applications (see<br>since the finite-state methodology and the event logic p<br>for the temporal interpretation of parallel structures.<br>The *Time Man* model addresses a number of impor-The *Time Map* model addresses a number of important issues that have arisen<br>
The *Time Map* model addresses a number of important issues that have arisen<br>
connection with phonological theories and speech recognition. Firs

for the temporal interpretation of parallel structures.<br>The *Time Map* model addresses a number of important issues that have arisen<br>in connection with phonological theories and speech recognition. Firstly, it provides The *Time Map* model addresses a number of important issues that have arisen<br>in connection with phonological theories and speech recognition. Firstly, it provides<br>a computational linguistic solution to the new word problem in connection with phonological theories and speech recognition. Firstly, it provides<br>a computational linguistic solution to the new word problem in speech recognition<br>by using a complete finite-state phonotactics of the l a computational linguistic solution to the new word problem in speech recognition<br>by using a complete finite-state phonotactics of the language to define the notion of<br>well-formedness. Secondly, it provides the phonologica by using a complete finite-state phonotactics of the language to define the notion of well-formedness. Secondly, it provides the phonological description with a temporal interpretation in terms of an event logic which not well-formedness. Secondly, it provides the phonological description with a temporal<br>interpretation in terms of an event logic which not only deals with abstract phono-<br>logical examples but also with concrete speech tokens. interpretation in terms of an event logic which not only deals with abstract phonological examples but also with concrete speech tokens. Thirdly, coarticulation and other phonological processes are modelled in a multiline logical examples but also with concrete speech tokens. Thirdly, coarticulation and<br>other phonological processes are modelled in a multilinear representation by provid-<br>ing an interpretation of overlap and gap phonomenon av other phonological processes are modelled in a multilinear representation by providing an interpretation of overlap and gap phonomenon avoiding a rigid segmentation into non-overlapping phonemes. Fourthly, the model copes ing an interpretation of overlap and gap phonomenon avoiding a rigid segmentation<br>into non-overlapping phonemes. Fourthly, the model copes with underspecification<br>by employing constraint relaxation and constraint enhanceme into non-overlapping phonemes. Fourthly, the model copes with underspecification<br>by employing constraint relaxation and constraint enhancement. Finally, since the<br>model is knowledge based, it has not been pre-tuned to any by employing constraint relaxation and constraint enhancement. Finally, since the model is knowledge based, it has not been pre-tuned to any particular speaker or any particular corpus, although ways in which this could be In model is knowledge based, it has not been pre-tuned to any particular speaker or any particular corpus, although ways in which this could be done using statistical information were discussed.

The model has been fully implemented and tested in an incremental linguistic information were discussed.<br>The model has been fully implemented and tested in an incremental linguistic<br>speech-recognition system. In that system, the *Time Map* model provided the formal<br>foundation for the phonological p The model has been fully implemented and tested in an incremental linguistic<br>speech-recognition system. In that system, the *Time Map* model provided the formal<br>foundation for the phonological parsing component, which was speech-recognition system. In that system, the *Time Map* model provided the formal foundation for the phonological parsing component, which was interfaced with an autonomous feature-extraction component (Hübener  $\&$  Car *Phil. Trans. R. Soc. Lond.* A (2000)

*Finite-statemodels,eventlogicsand statistics* <sup>1265</sup> Downloaded from rsta.royalsocietypublishing.org

**NEERING**<br>ES a word parser. However, since the model is independent of these other components, a word parser. However, since the model is independent of these other components,<br>it should be immediately possible to interface it directly—or use it in parallel—<br>with other multilinear recognition systems, such as those it should be immediately possible to interface it directly—or use it in parallel—<br>with other multilinear recognition systems, such as those suggested by Kirchhoff<br>(1996) or King *et al.* (1998), in which the paradigms bein it should be immediately possible to interface it directly—or use it in parallel with other multilinear recognition systems, such as those suggested by Kirchhoff (1996) or King *et al.* (1998), in which the paradigms being followed are the hidden Markov approach and the connectionist approach, respecti

(1996) or King *et al.* (1998), in which the paradigms being followed are the hidden Markov approach and the connectionist approach, respectively. Although the *Time Map* model was developed originally in the phonetic and Markov approach and the connectionist approach, respectively. Although the *Time*  $Map$  model was developed originally in the phonetic and phonological knowledge domains, it does generalize to higher levels in the prosodic *Map* model was developed originally in the domains, it does generalize to higher levels the need for a level-specific segmentation.

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**PHILOSOPHICAL**<br>TRANSACTIONS

ATHEMATICAL

Press.

*Discussion*<br>
S. J. Young (*University of Cambridge, UK*). The main focus of your presentation<br>
was on the recognition of new words. But are new words hard to recognize? It seems S. J. YOUNG (*University of Cambridge, UK*). The main focus of your presentation was on the recognition of new words. But are new words hard to recognize? It seems to me that the most challenging outstanding problems in s S. J. YOUNG (*University of Cambridge, UK*). The main focus of your presentation was on the recognition of new words. But are new words hard to recognize? It seems to me that the most challenging outstanding problems in s was on the recognition of new words. But are new words hard to recognize? It seems<br>to me that the most challenging outstanding problems in speech recognition lie not<br>in word models but in language modelling. An important u

to me that the most challenging outstanding problems in speech recognition lie not<br>in word models but in language modelling. An important useful property of the<br>standard statistical speech-recognition architecture is *boot* in word models but in language modelling. An important useful property of the standard statistical speech-recognition architecture is *bootstrapping*, that is, using a model trained on a small dataset to annotate a much la standard statistical speech-recognition<br>model trained on a small dataset to a<br>be used for training a larger model.

model training a larger model.<br>be used for training a larger model.<br>J. CARSON-BERNDSEN. Using phonotactic models reduces the need for training our<br>speech recognizer on a large corpus, because of the linguistic generality o speech recognizer on a larger model.<br>J. CARSON-BERNDSEN. Using phonotactic models reduces the need for training our<br>speech recognizer on a large corpus, because of the linguistic generality of the con-<br>straints. For exampl J. CARSON-BERNDSEN. Using phonotactic models reduces the need for training our<br>speech recognizer on a large corpus, because of the linguistic generality of the con-<br>straints. For example, we noticed that a consonant sequen speech recognizer on a large corpus, because of the linguistic generality of the constraints. For example, we noticed that a consonant sequence defined by our German model,  $/$ -lnst $/$ , did not occur in any word in the di straints. For example, we noticed that a consonant sequence defined by our German model, /-lnst/, did not occur in any word in the dictionary. But intuition suggested it would be phonotactically possible in, for example, t model, /-lnst/, did not occur in any word in the dictionary. But intuition suggested<br>it would be phonotactically possible in, for example, the coinage *kölnst du?*, *Do you*<br>*cologne?*, which native speakers, when asked, a

D. KAZAKOV (*University of York, UK*). How well does this approach perform compared with methods based on analogy? For example, one accepts *blant* as a likely pared with methods based on analogy? For example, one accepts *blant* as a likely word because one knows that *plant* plaster and *bluster* are words D. KAZAKOV (*University of York, UK*). How well does this approach pared with methods based on analogy? For example, one accepts *bl* word, because one knows that *plant, plaster* and *bluster* are words.

pared with methods based on analogy? For example, one accepts *blant* as a likely<br>word, because one knows that *plant, plaster* and *bluster* are words.<br>J. CARSON-BERNDSEN. The two approaches are complementary: the feature J. CARSON-BERNDSEN. The two approaches are complementary: the features and multilinear representations of my system could be employed in the computation of analogy.

H. Alshawi (*AT & T Laboratories, Florham Park, NJ, USA*). For the recognition of foreign names and loan-words, do you envisage a universal phonotactic model, or several language-specific models applied in parallel?

of foreign names and foan-words, do you envisage a universal phonotactic model, or<br>several language-specific models applied in parallel?<br>J. CARSON-BERNDSEN. Since we are already using different models for different<br>languag Several language-speeme models applied in parallel.<br>
J. CARSON-BERNDSEN. Since we are already using different models for different<br>
languages, we could use several of them as parallel sub-models in that case. I do not<br>
thi languages, we could use several of them as parallel sub-models in that case. I do not think a single universal model would be feasible.

F. PEREIRA (*AT & T Laboratories, Florham Park, NJ, USA*). Another advantage of the standard speech-recognition architecture is that multiple sources of uncertainty The standard speech-recognition architecture is that multiple sources of uncertainty<br>the standard speech-recognition architecture is that multiple sources of uncertainty<br>can be resolved by exploiting a mathematically well F. PEREIRA  $(AT \& T$  *Laboratories, Florham Park, NJ, USA*). Another advantage of<br>the standard speech-recognition architecture is that multiple sources of uncertainty<br>can be resolved by exploiting a mathematically well-defi the standard speech-recognition architecture is that multiple sources of uncertainty<br>can be resolved by exploiting a mathematically well-defined combination of prob-<br>abilistic models of different levels of structure. For e can be resolved by exploiting a mathematically well-defined combination of probabilistic models of different levels of structure. For example, voicing detection can be rather unreliable, but the word model could ameliorate abilistic models of different levels of structure. For example, voicing detection can<br>be rather unreliable, but the word model could ameliorate the uncertainty of the<br>acoustic analysis.

 $\blacktriangleright$  J. CARSON-BERNDSEN. Our model has three mechanisms for coping with such uncer- $\blacksquare$  tainty. First, there is the differential weighting of constraints and the relaxation of, for J. CARSON-BERNDSEN. Our model has three mechanisms for coping with such uncertainty. First, there is the differential weighting of constraints and the relaxation of, for example, infrequency constraints. Second, by using u tainty. First, there is the differential weighting of constraints and the relaxation of, for<br>example, infrequency constraints. Second, by using underspecified representations,<br>variable or uncertain features can be omitted. example, infrequency constraints. Second, by using underspecified representations,<br>variable or uncertain features can be omitted. Third, we try to defer decisions until<br>late in the analysis process, to avoid incorrect comm variable or uncertain features can be omitted. Third, we try to defer decisions until<br>late in the analysis process, to avoid incorrect commitment at an earlier stage. In<br>this way, for example, phonotactic constraints could late in the analysis p<br>this way, for example<br>the signal analysis.

**MATHEMATICAL,<br>PHYSICAL**<br>& ENGINEERING

**PHILOSOPHICAL**<br>TRANSACTIONS ŏ