Speech Processing

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additional class slides for 2020-21

Module 6

Pattern matching

Orientation

- We're on a journey towards HMMs
  - Pattern **matching**
  - Extracting **features** from speech
  - Probabilistic **generative** modelling

What we are learning along the way

Dynamic programming
(in the form of Dynamic Time Warping)

The interaction between
- choice of model
- choice of features

Dynamic programming
(in the form of the Viterbi algorithm)

What you should already know

- Why the **waveform** is not good for pattern recognition

- Concept of a **feature vector**

- Let's start as simple as possible: whole word templates
  - But we already have to deal with sequences of **different lengths**

Source and filter are combined

But we only want the **filter**

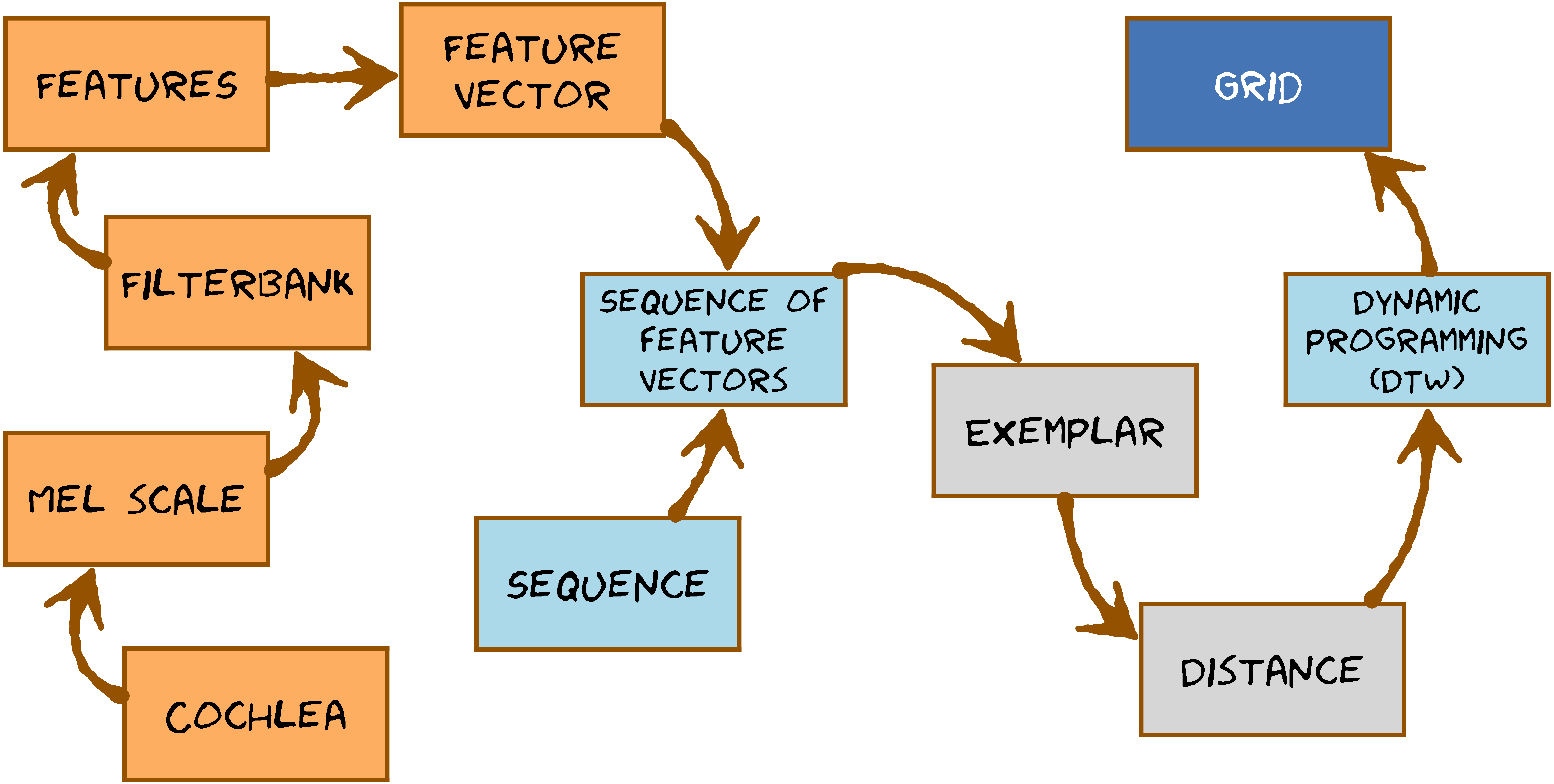
Speech waveforms change over time

Use short-term analysis

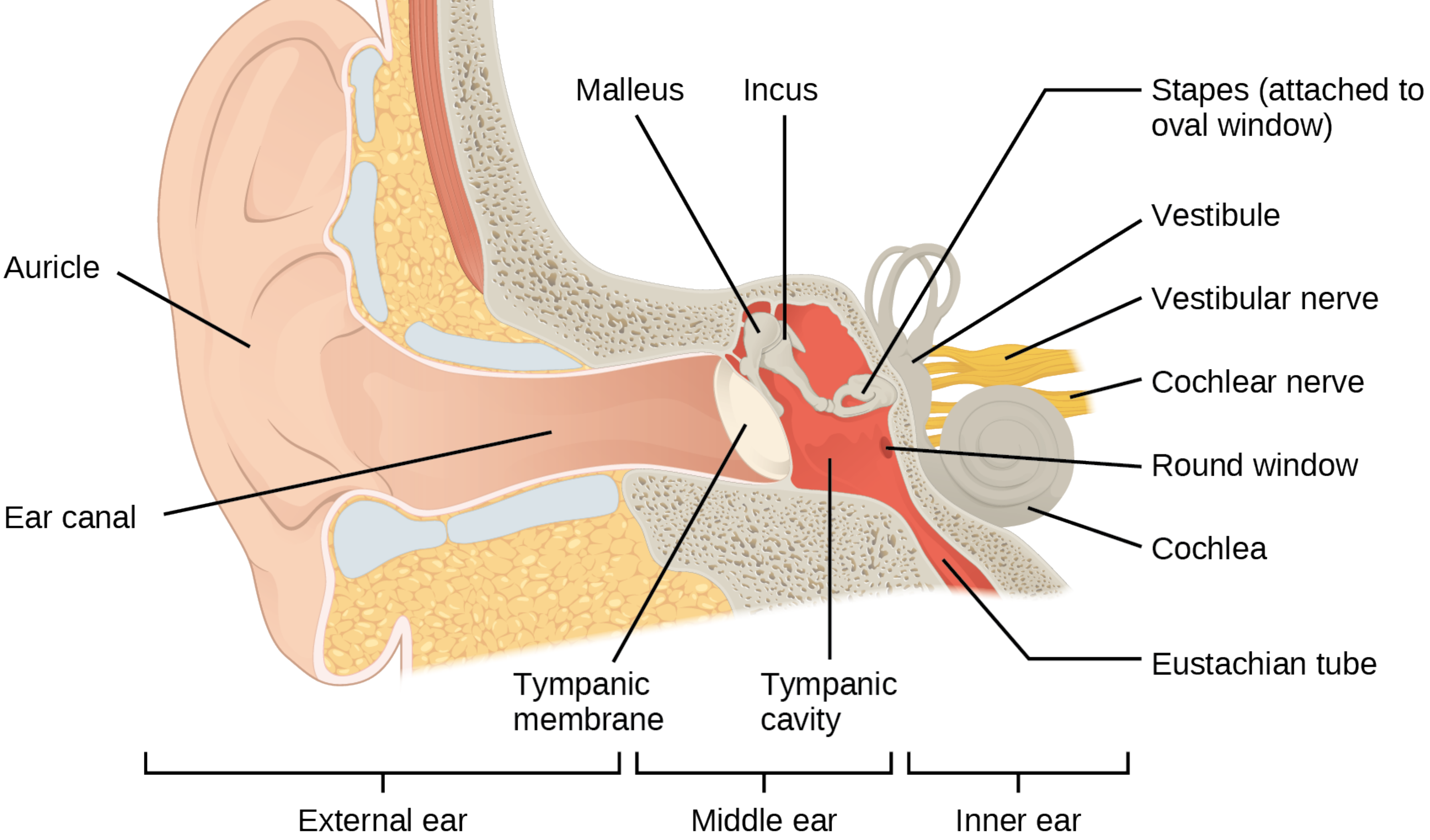
Extract features from frames of speech

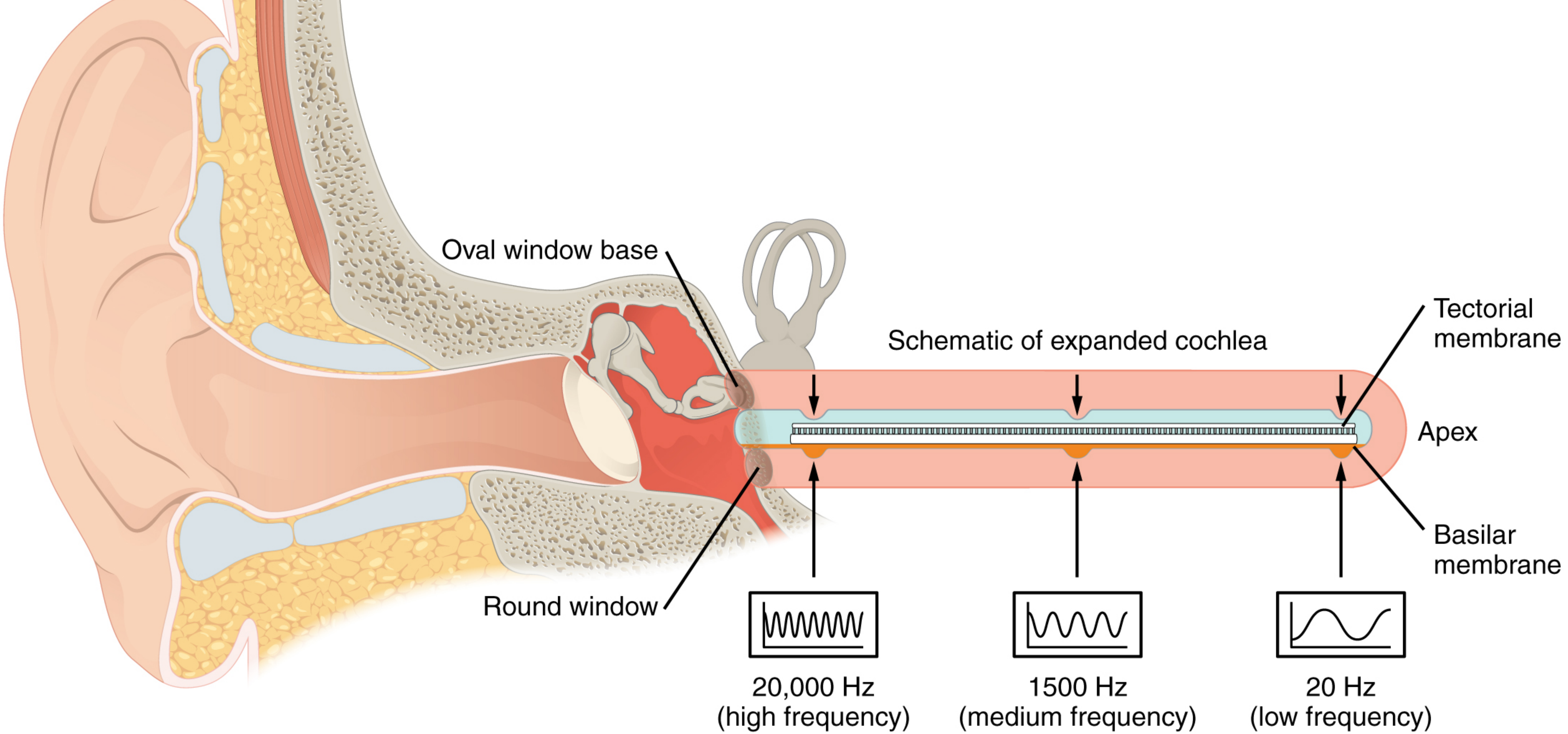
Finding an alignment between two sequences

- linear time warping
- non-linear ('dynamic') time warping

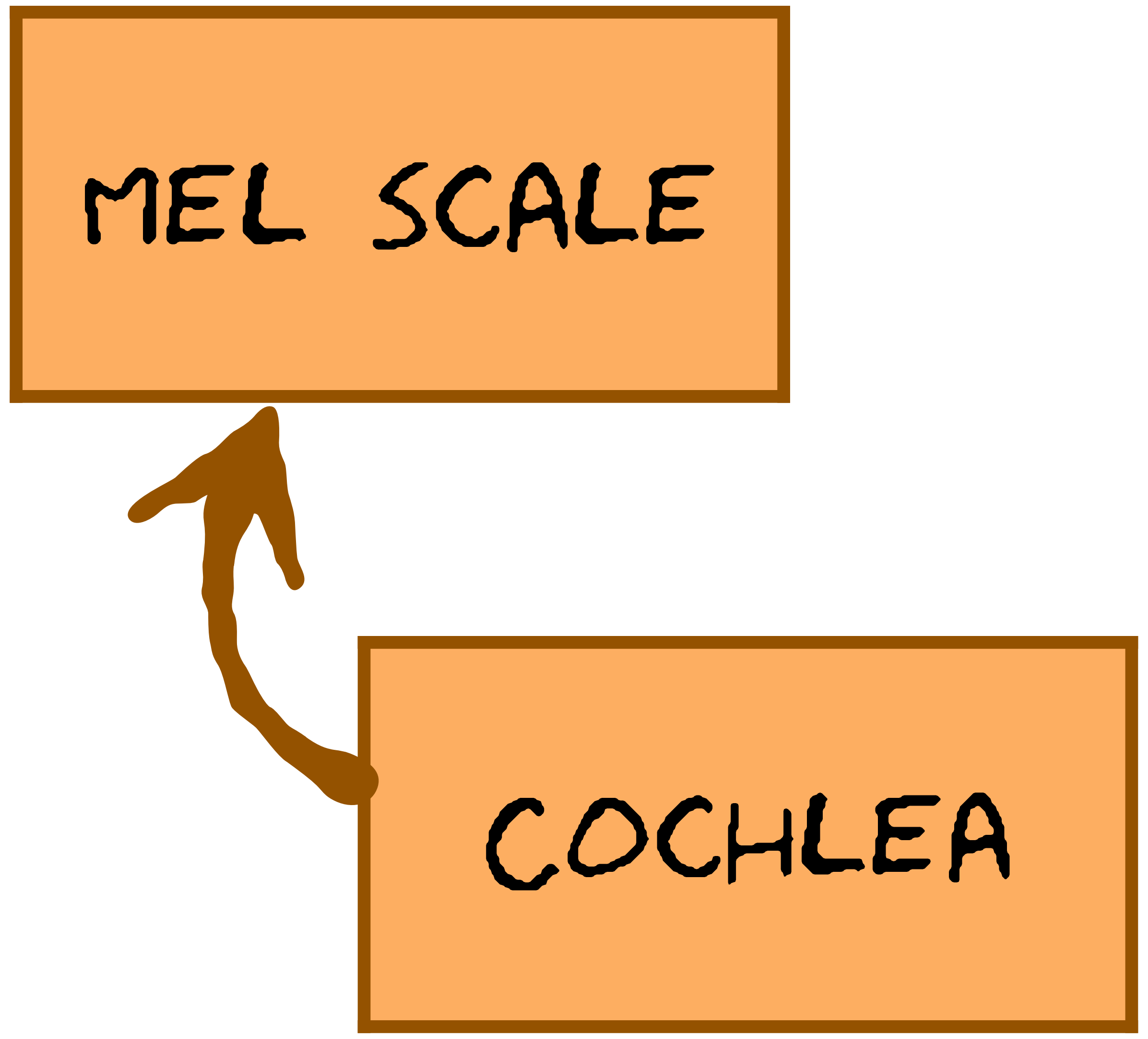

FEATURES
FEATURE VECTOR
GRID
FILTERBANK
SEQUENCE OF FEATURE VECTORS
DYNAMIC PROGRAMMING (DTW)
EXEMPLAR
MEL SCALE
SEQUENCE
DISTANCE
COCHLEA

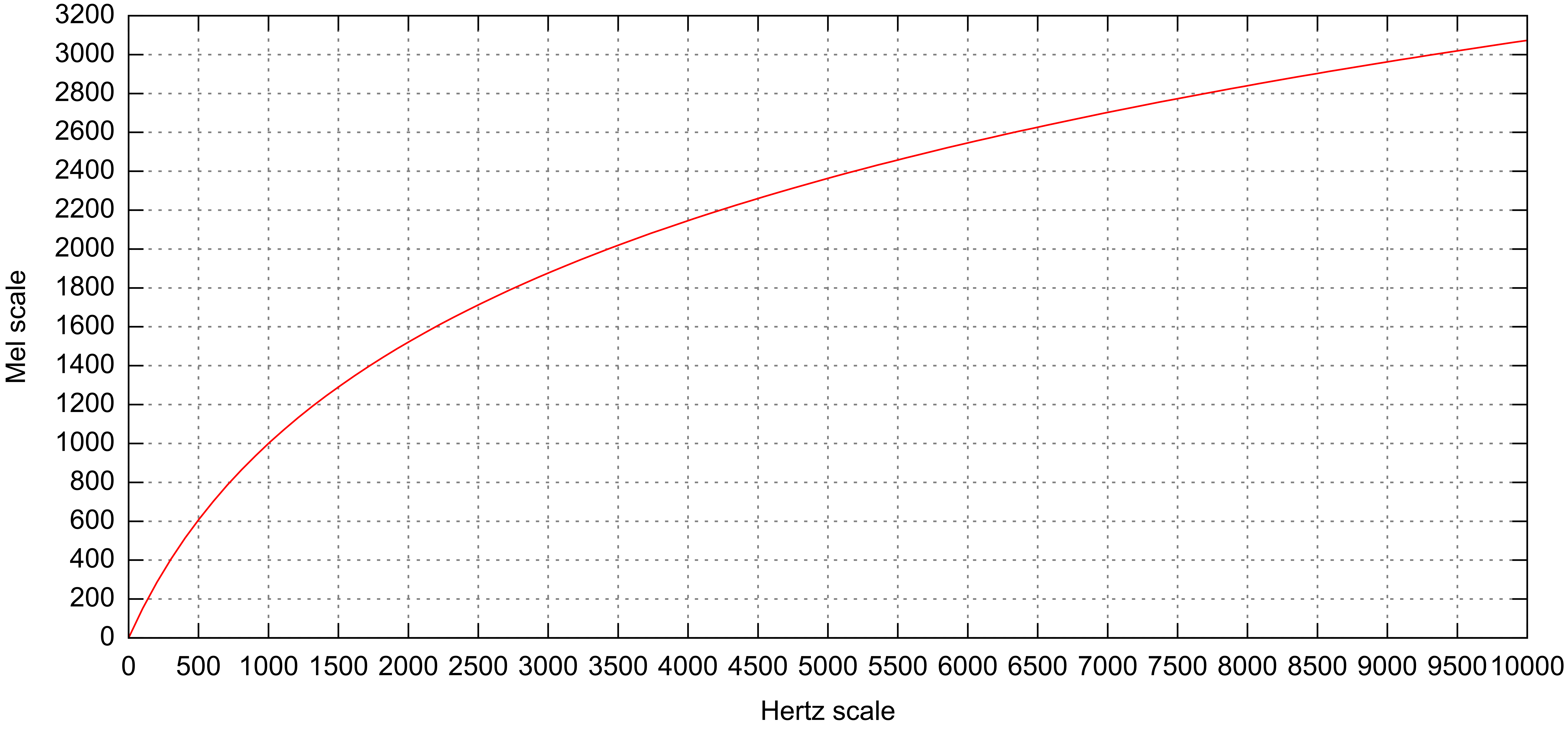
COCHLEA


Malleus
Incus
Stapes (attached to oval window)
Vestibule
Vestibular nerve
Cochlear nerve
Round window
Cochlea
Eustachian tube
Auricle
Ear canal
Tympanic membrane
Tympanic cavity
External ear
Middle ear
Inner ear



Oval window base
Schematic of expanded cochlea
Tectorial membrane
Apex
Basilar membrane
Round window
20,000 Hz
(high frequency)
1500 Hz
(medium frequency)
20 Hz
(low frequency)


MEL SCALE
COCHLEA


Mel scale
Hertz scale
0
200
400
600
800
1000
1200
1400
1600
1800
2000
2200
2400
2600
2800
3000
3200
500
1000
1500
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4500
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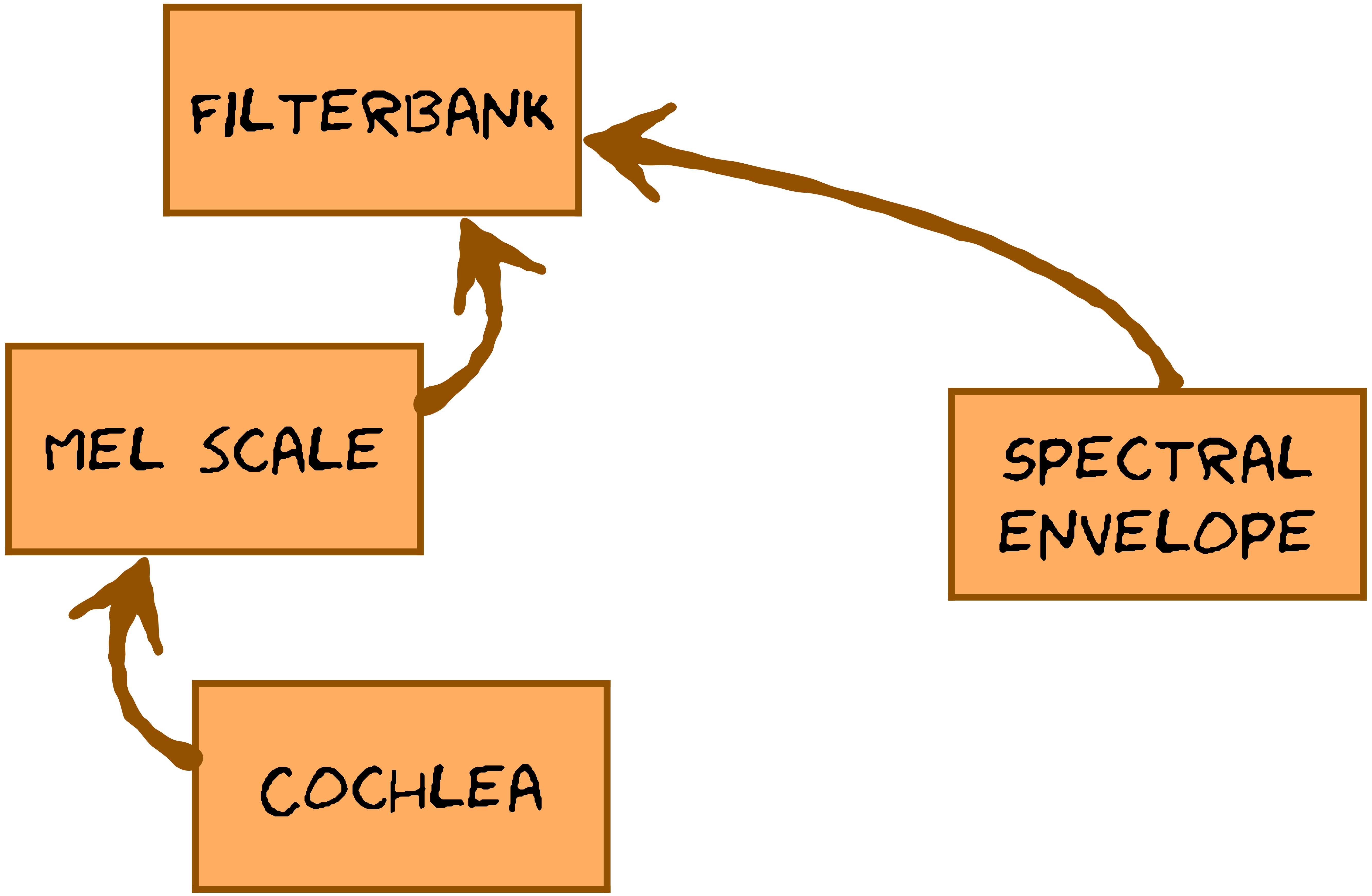
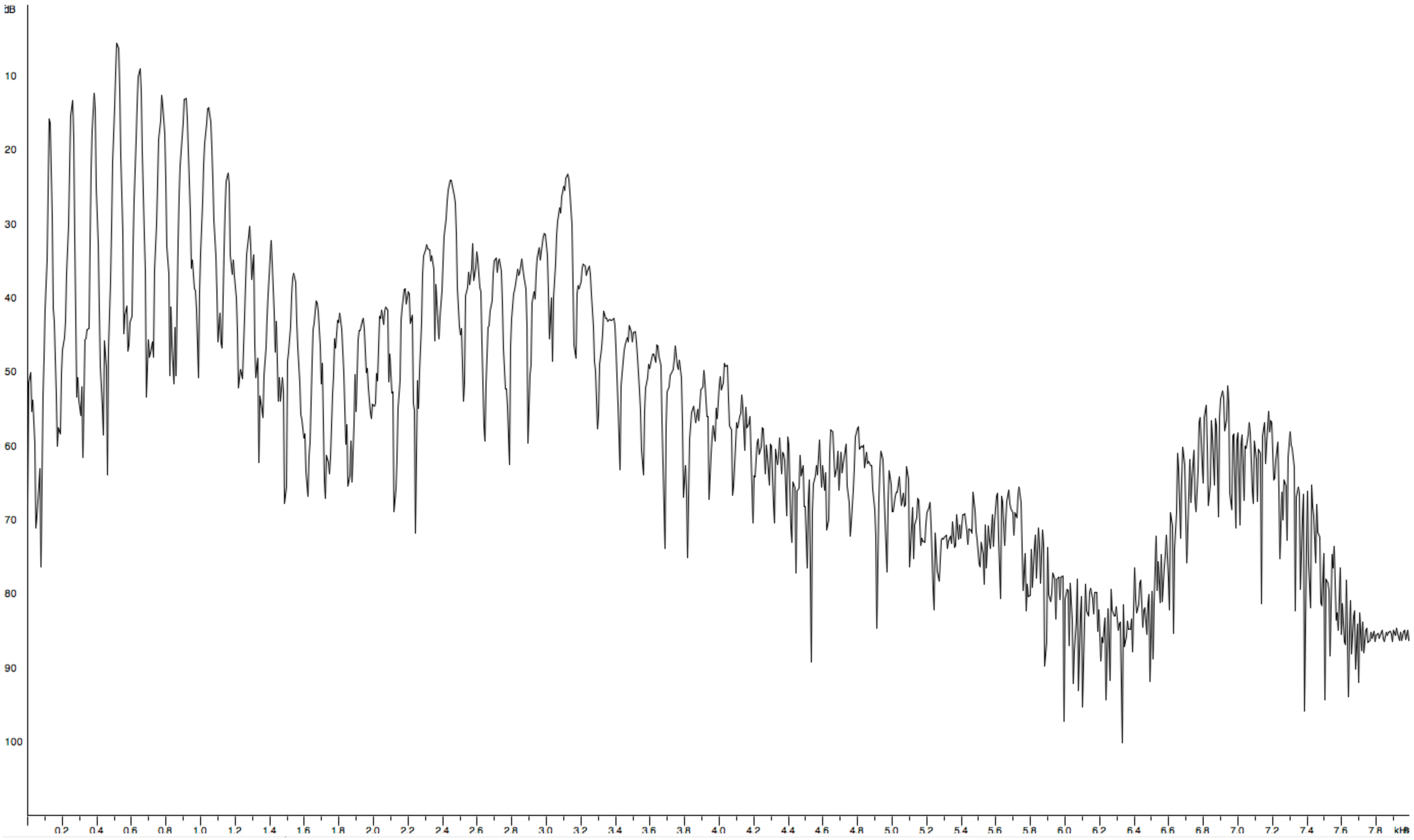
5500
6000
6500
7000
7500
8000
8500
9000
9500
10000

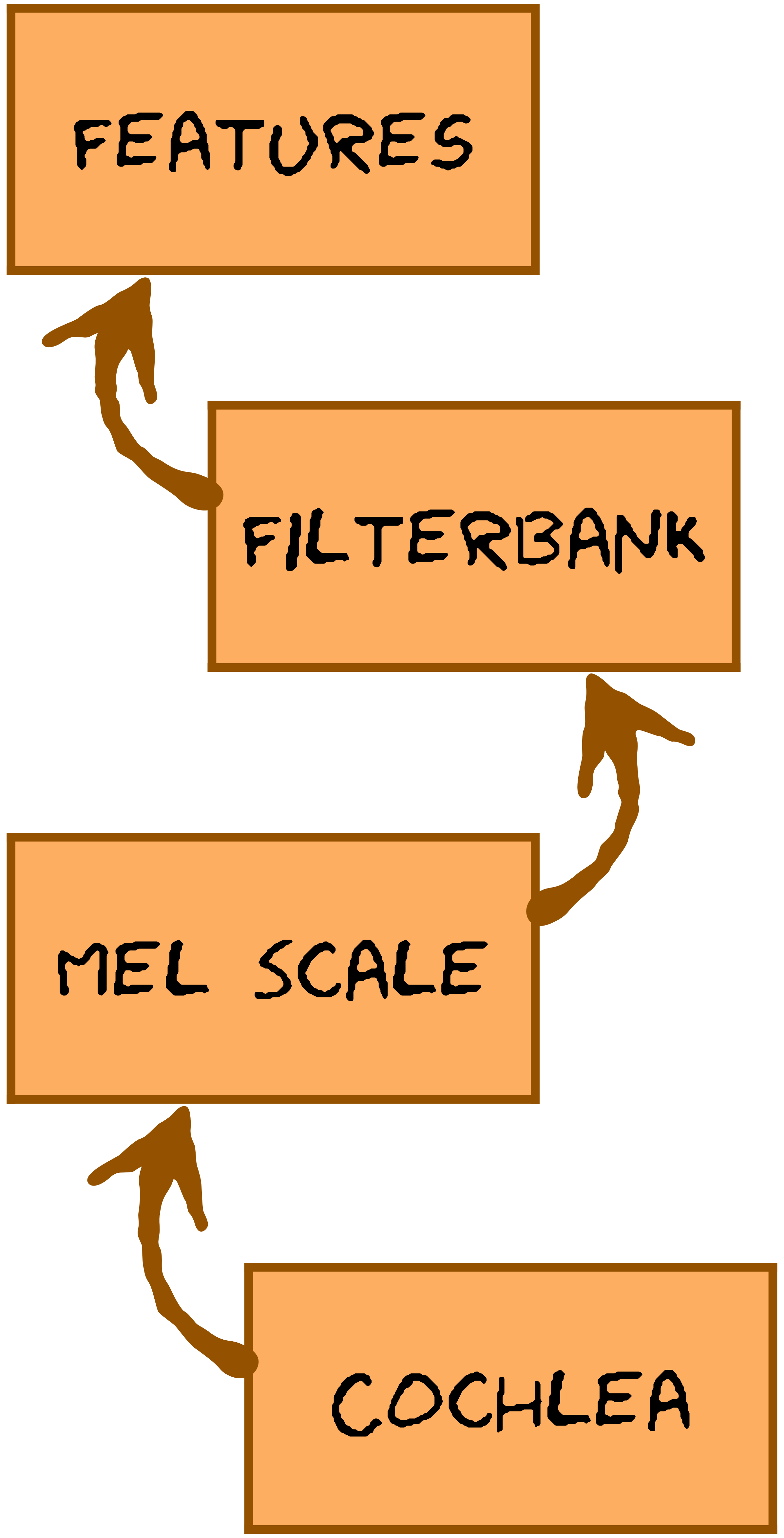

FILTERBANK
MEL SCALE
SPECTRAL ENVELOPE
COCHLEA

The auditory system is like a bank of bandpass filters: a “filterbank”

magnitude (log scale)

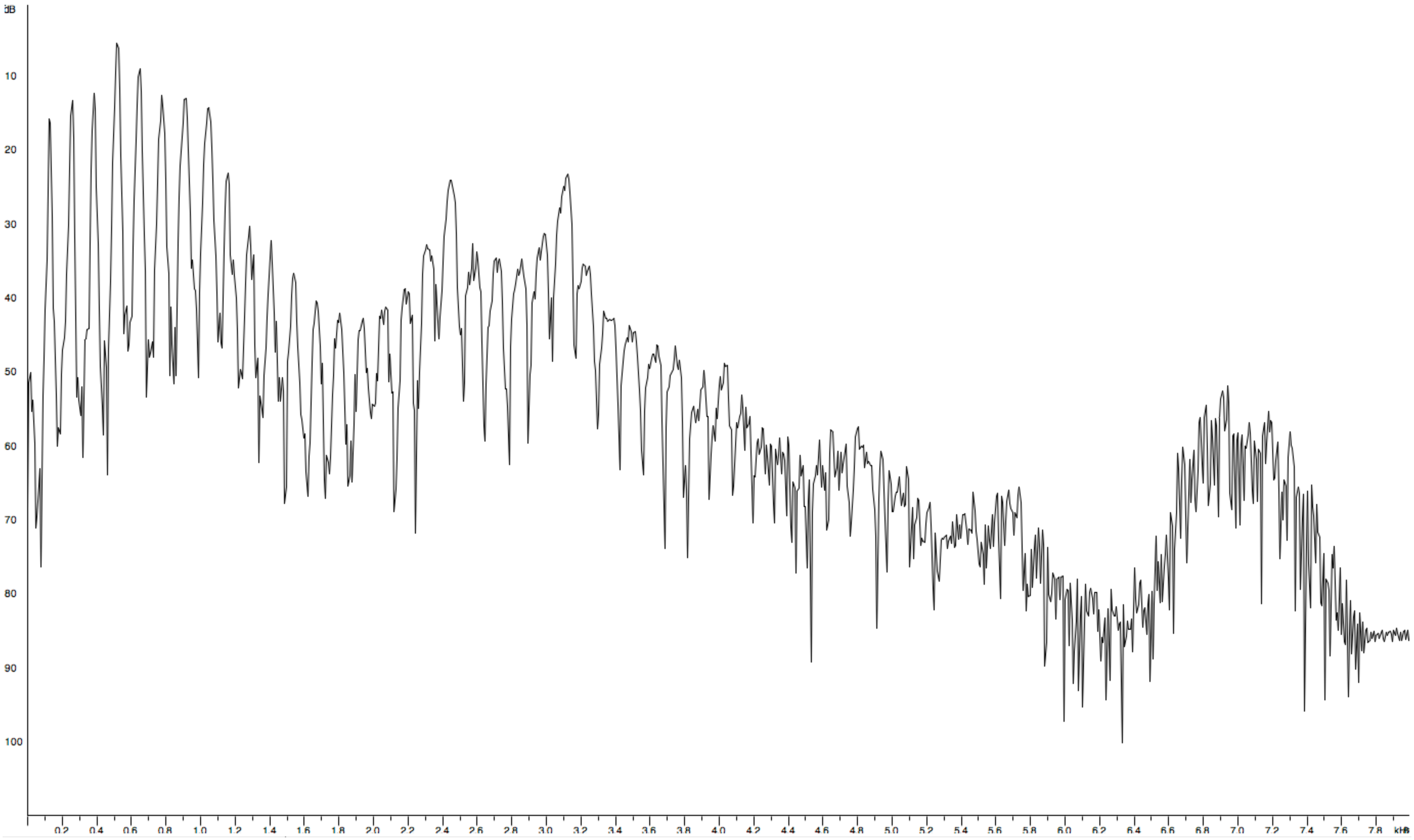


0 frequency 8kHz


FEATURES
FILTERBANK
MEL SCALE
COCHLEA

Each filter's output is a useful feature for doing Automatic Speech Recognition

magnitude (log scale)



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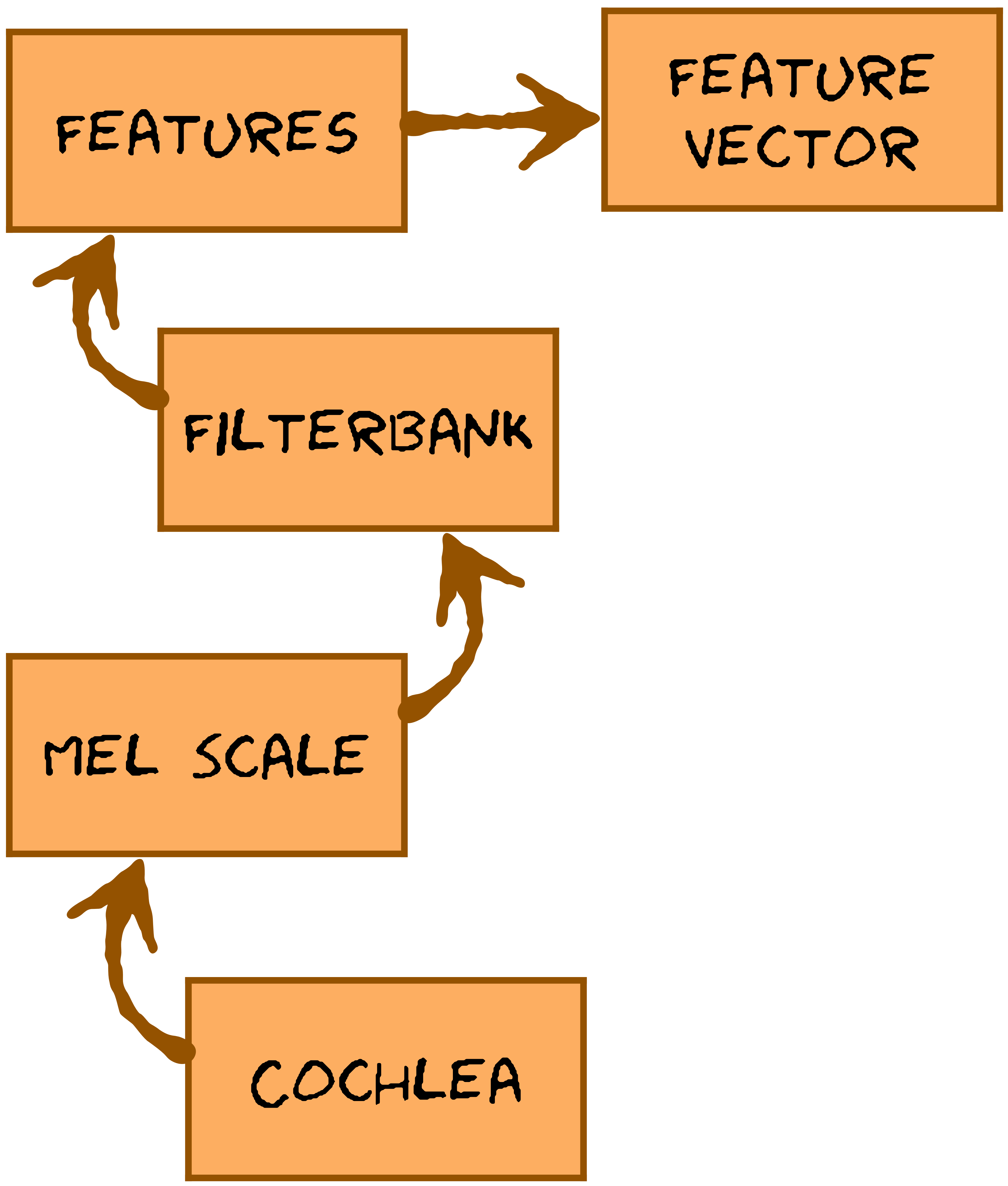
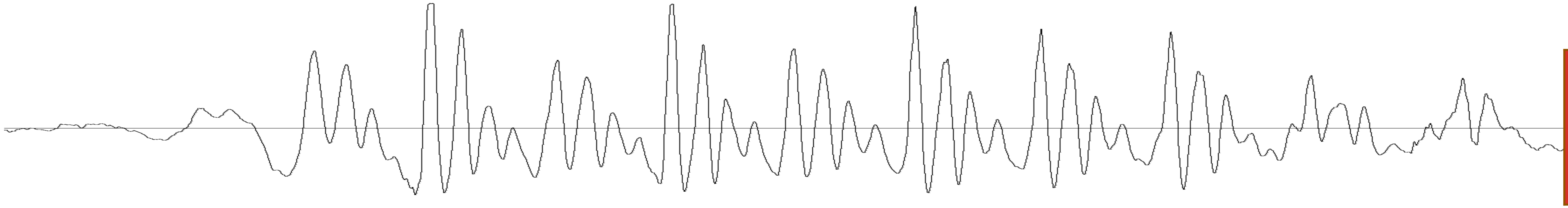
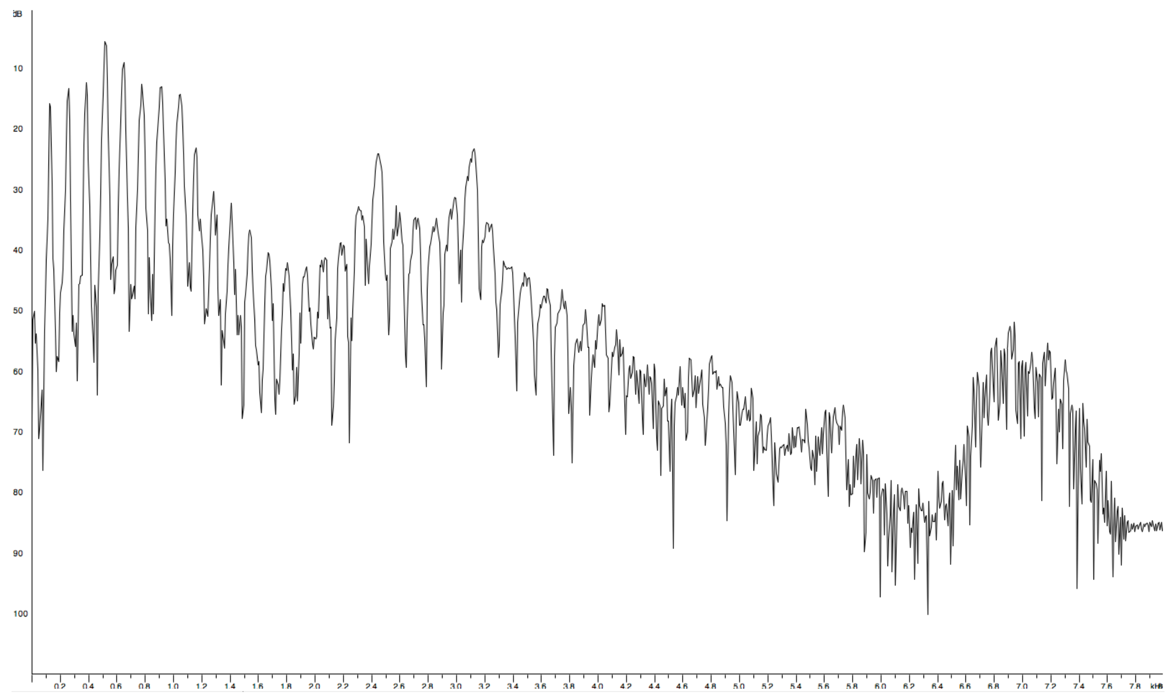

FEATURES
FEATURE VECTOR
FILTERBANK
MEL SCALE
COCHLEA

Filterbank features for one frame are speech are stored in a single vector

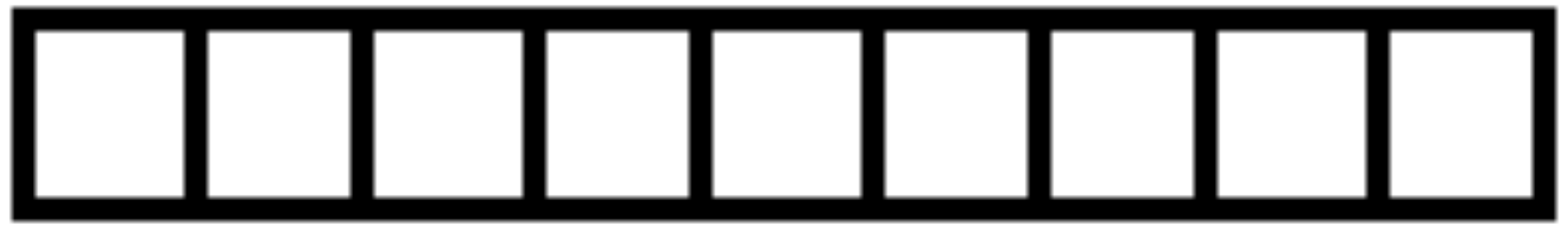


TIME DOMAIN

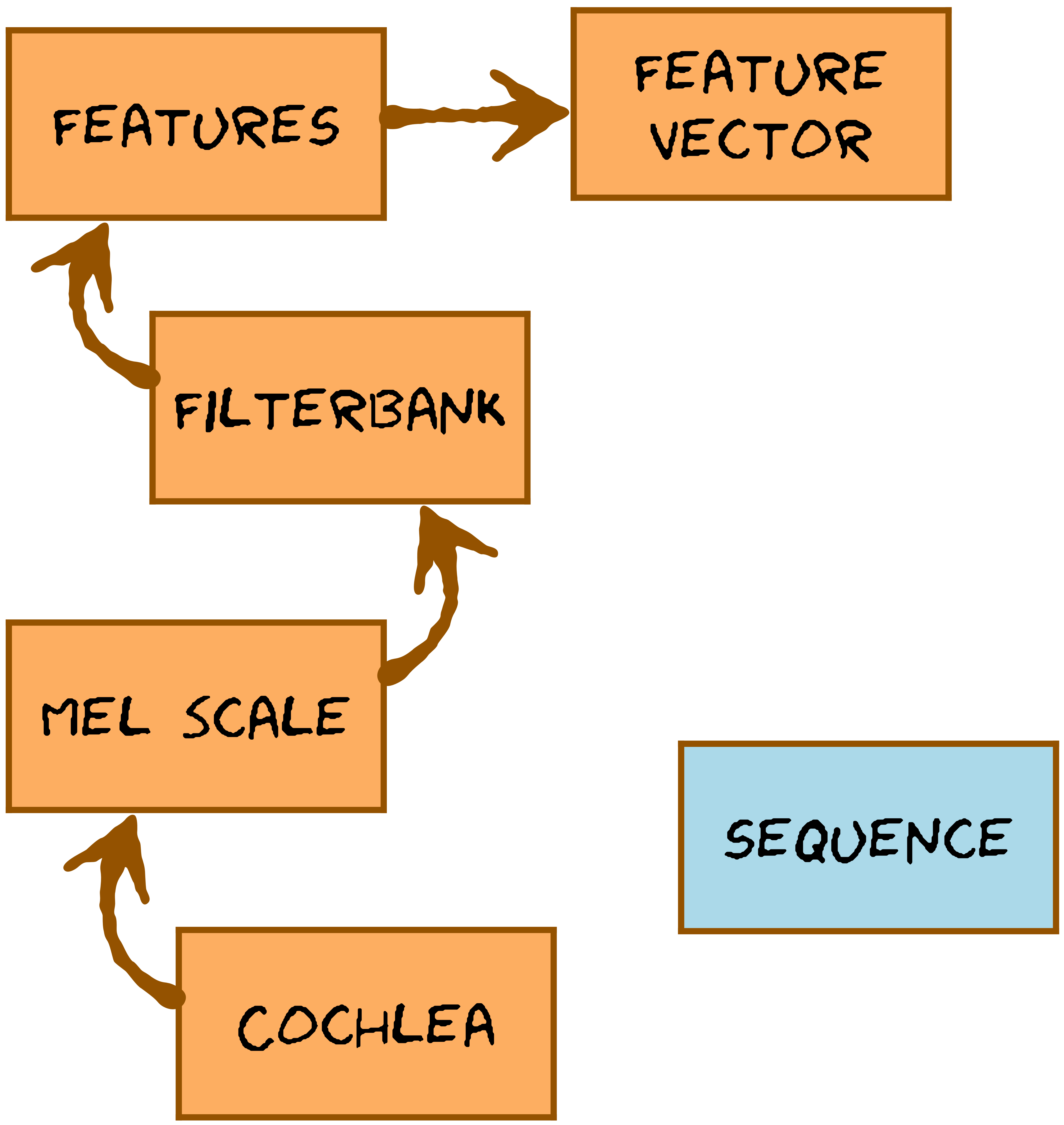
FEATURES



FREQUENCY DOMAIN



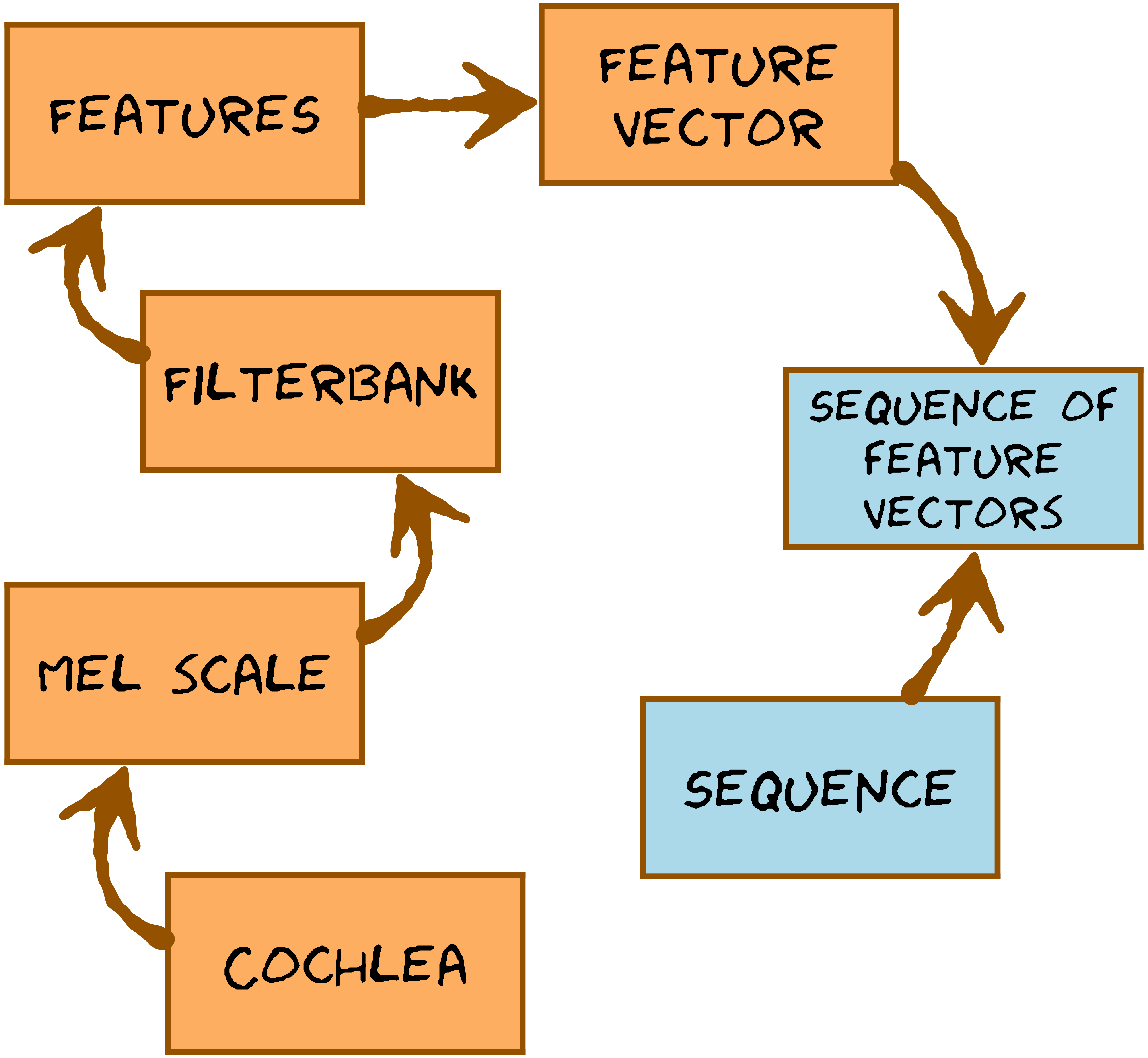
FEATURE VECTOR


FEATURES
FEATURE VECTOR
FILTERBANK
MEL SCALE
COCHLEA
SEQUENCE

SEQUENCE

Sequences are *everywhere* in language

- We've already seen
  - a waveform is a sequence of **samples**
  - a waveform can be analysed as a sequence of overlapping analysis **frames**
  - a sentence is a sequence of **words**
  - a spoken word is a sequence of **phones**
  - a written word is a sequence of **letters**
- Now we have
  - from each frame we extract a feature vector
  - so a waveform becomes a **sequence of feature vectors**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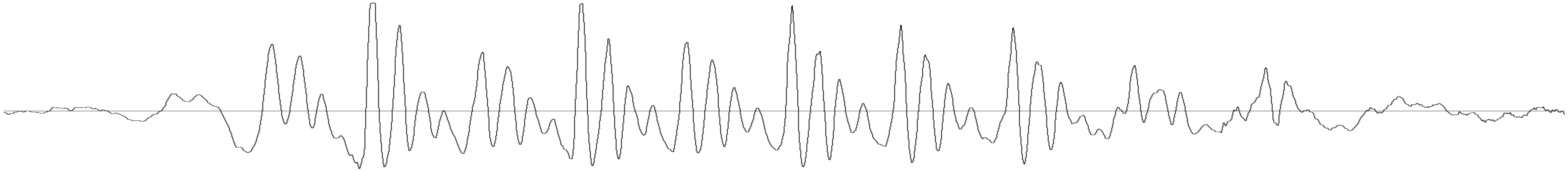
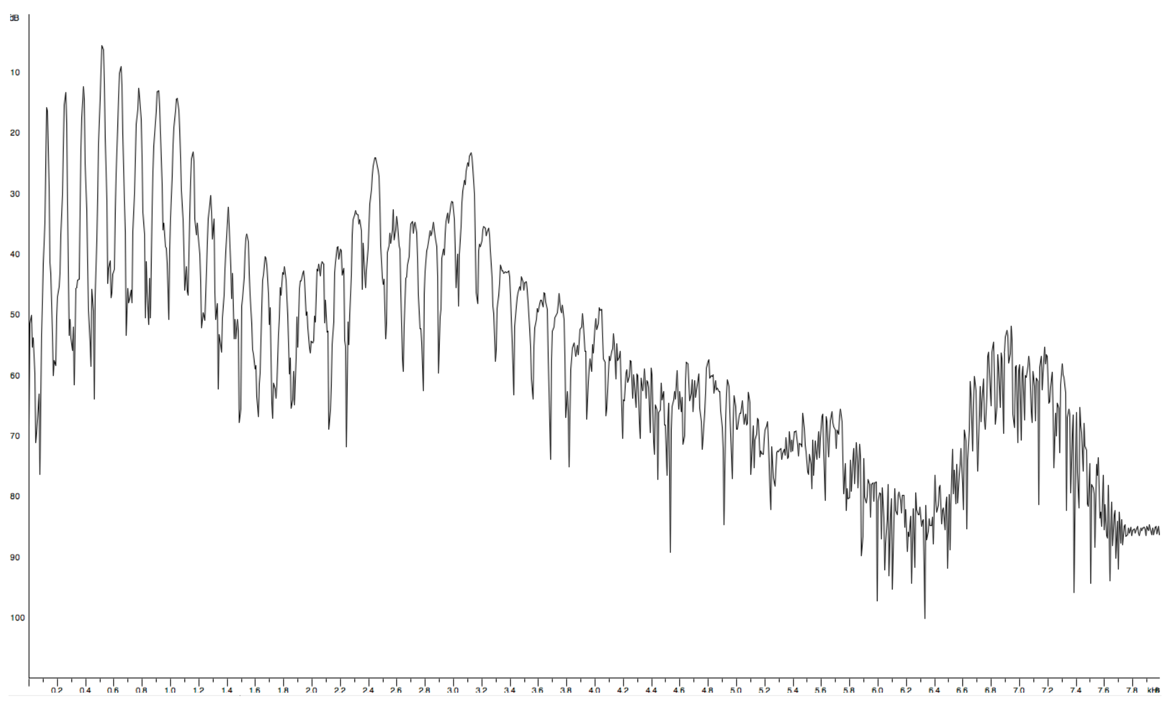
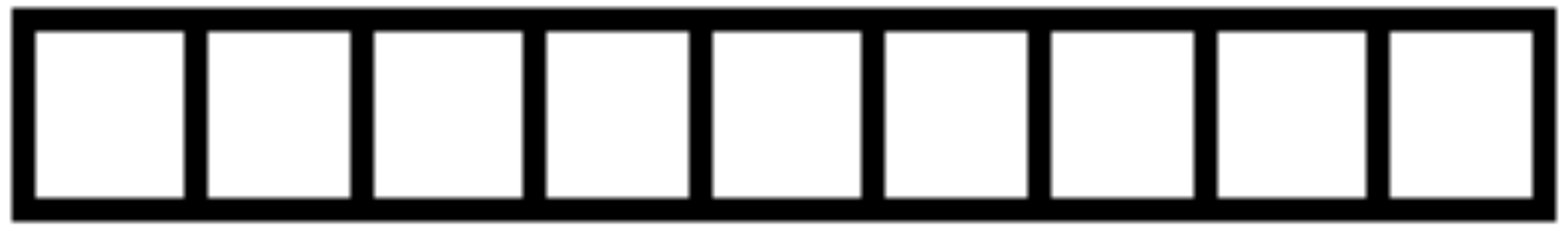
FEATURE VECTOR
FILTERBANK
SEQUENCE OF FEATURE VECTORS
MEL SCALE
SEQUENCE
COCHLEA

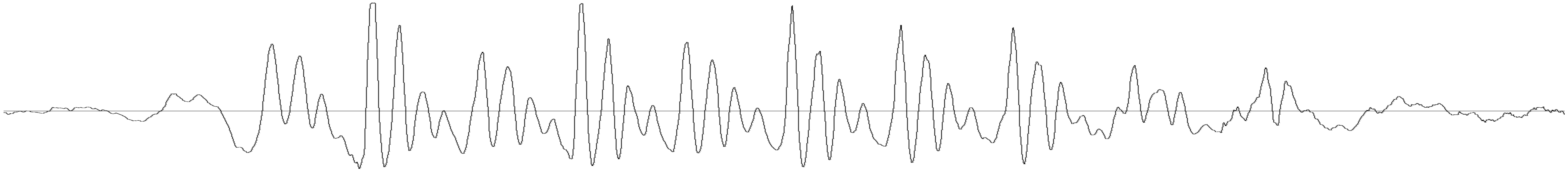
Filterbank features for one frame are speech are stored in a single vector

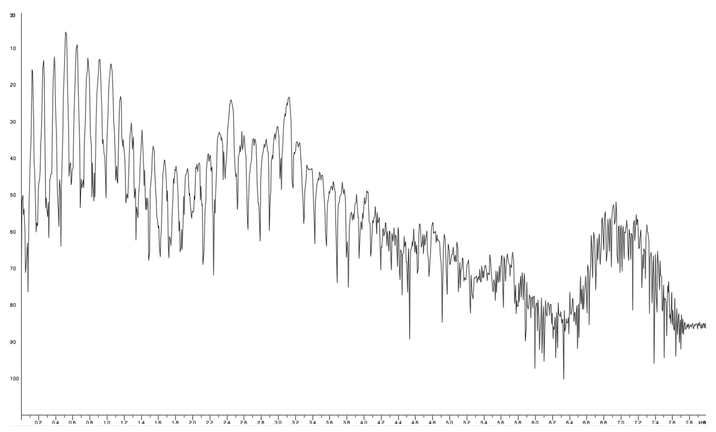






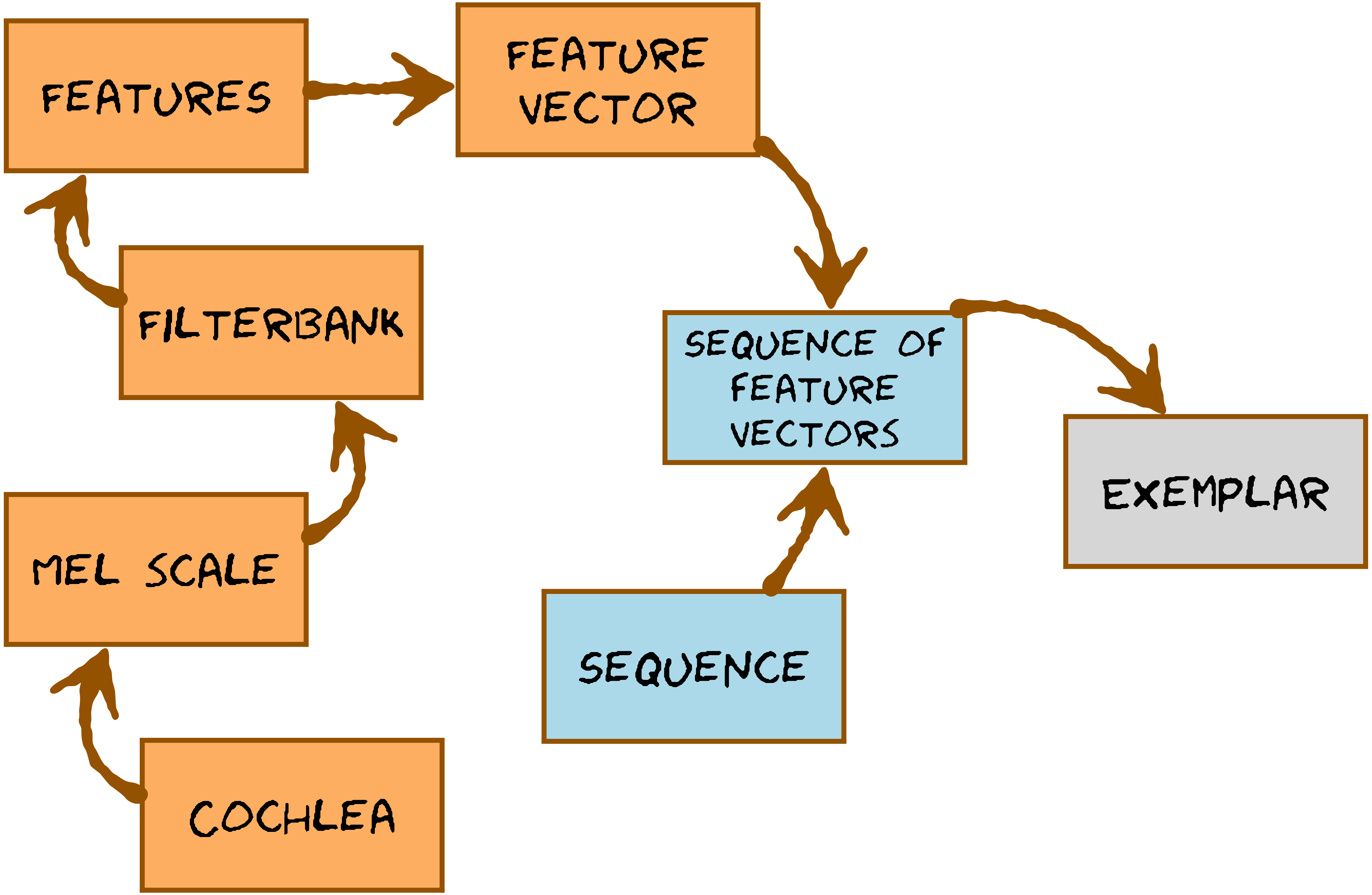
Filterbank features for automatic speech recognition



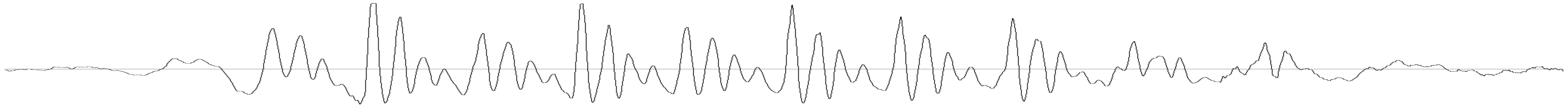


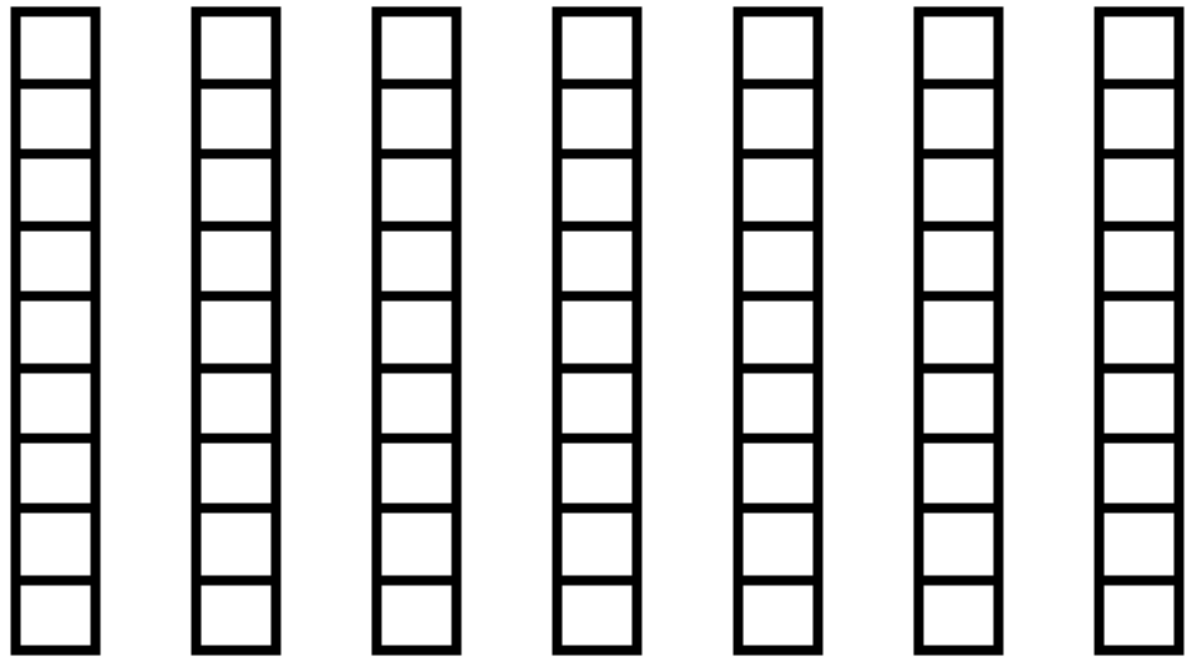
SEQUENCE OF FEATURE VECTORS

Filterbank features for automatic speech recognition

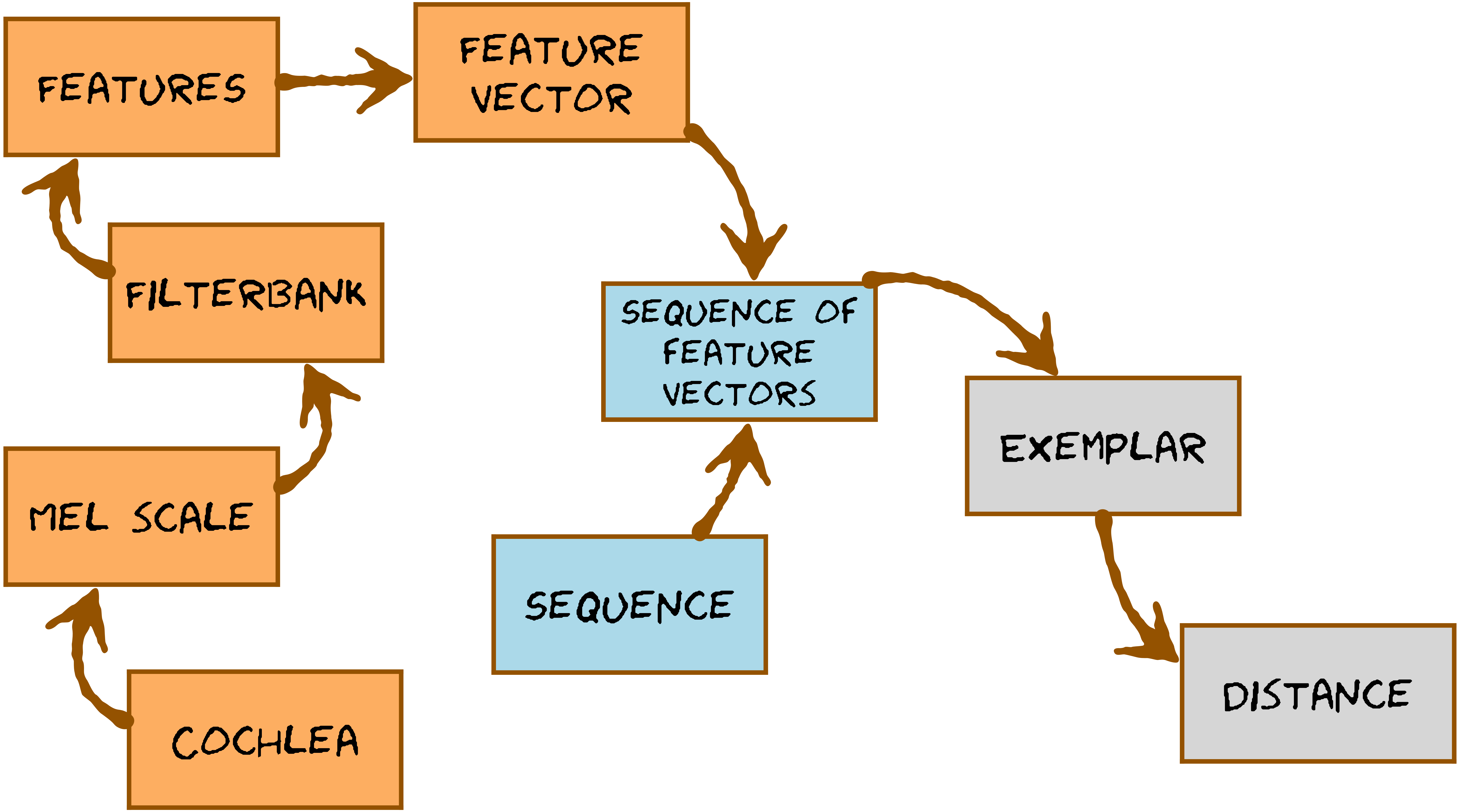

FEATURES
FEATURE VECTOR
FILTERBANK
SEQUENCE OF FEATURE VECTORS
EXEMPLAR
MEL SCALE
SEQUENCE
COCHLEA

“three”





EXEMPLAR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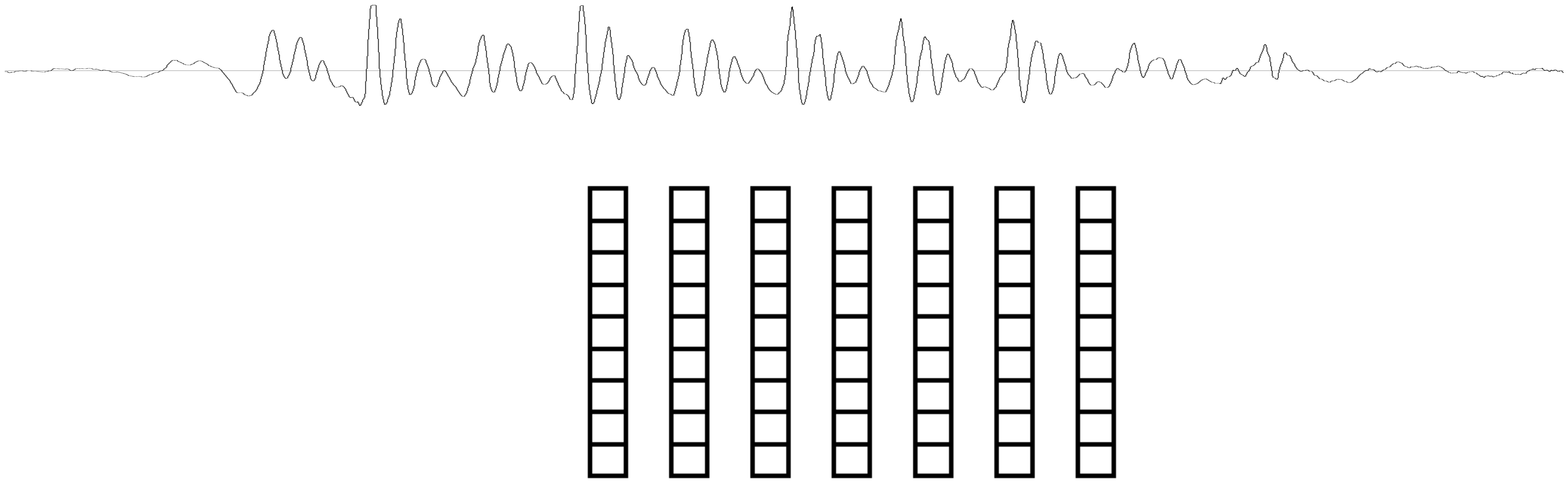
FEATURE VECTOR
FILTERBANK
SEQUENCE OF FEATURE VECTORS
EXEMPLAR
MEL SCALE
SEQUENCE
DISTANCE
COCHLEA

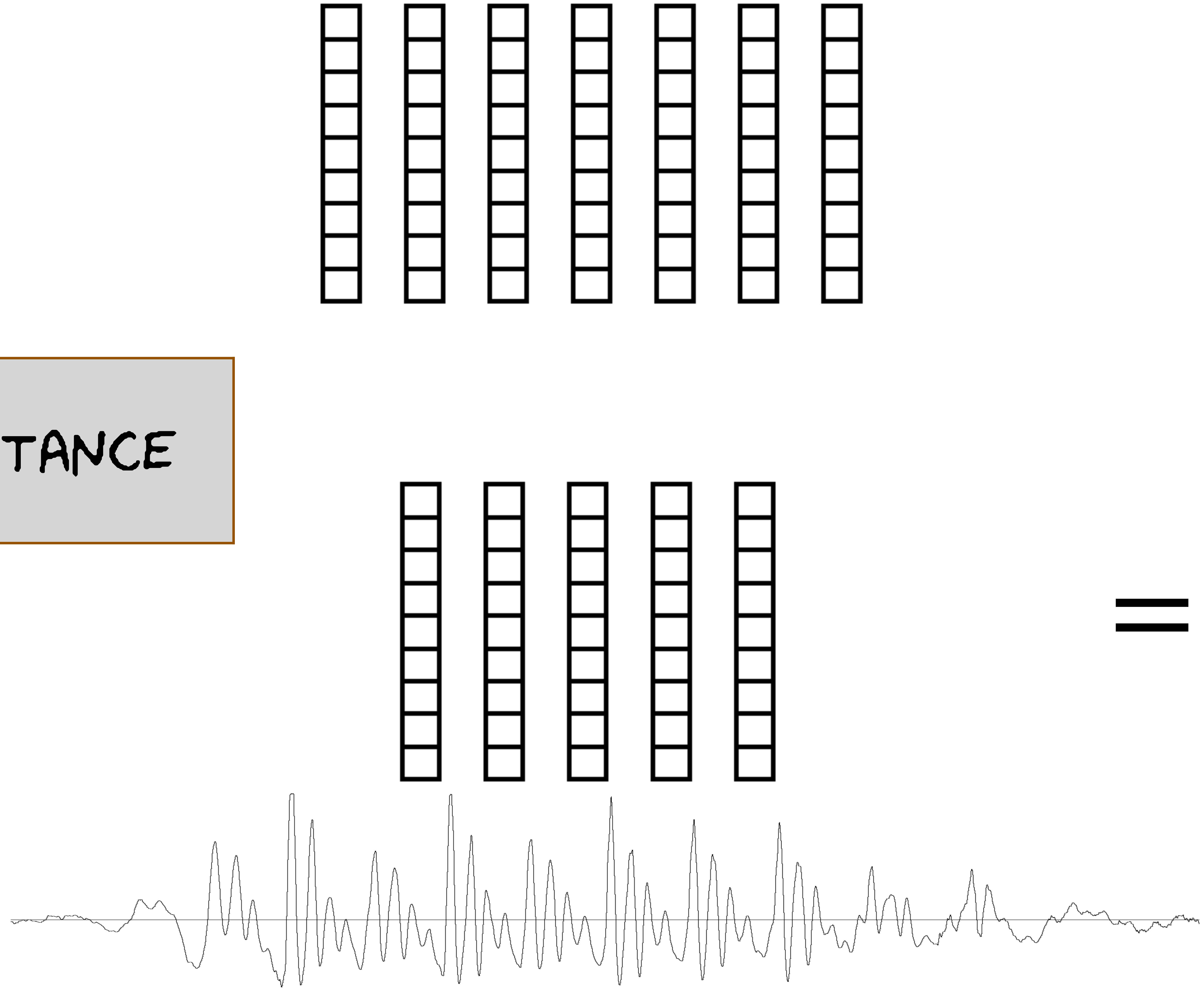
"three"

EXEMPLAR



EXEMPLAR

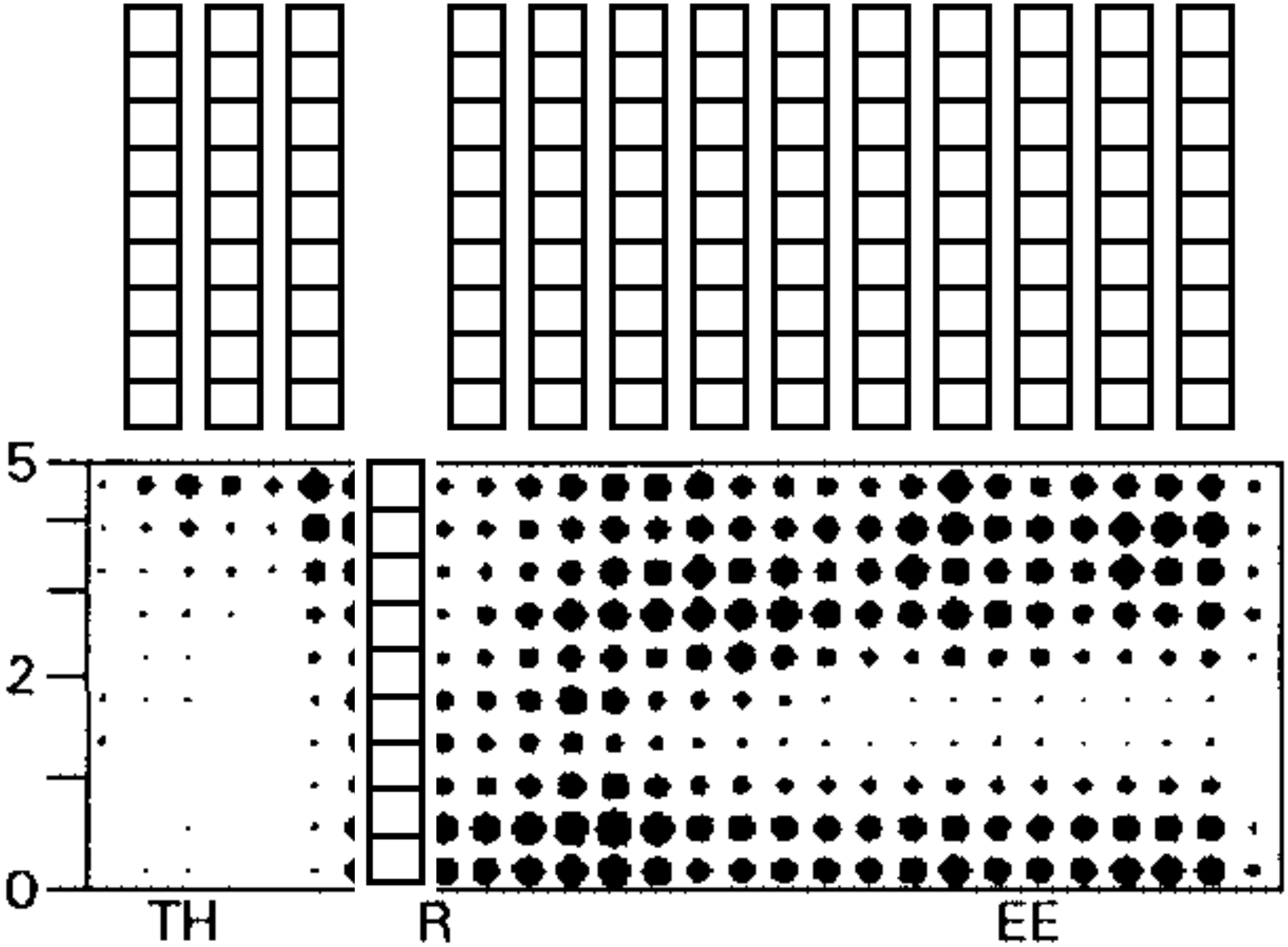
“three”



“???”

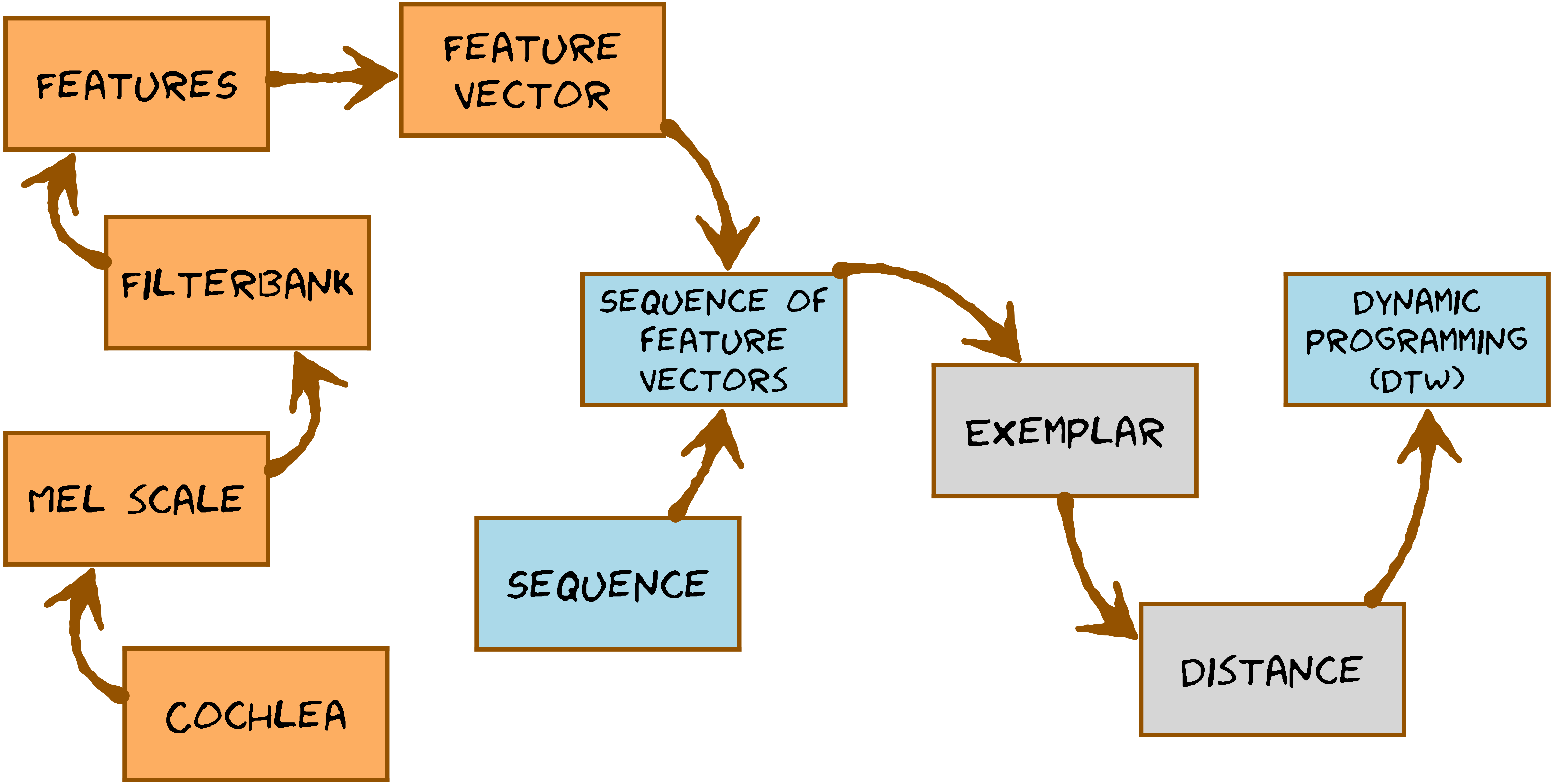
DISTANCE

global distance $= \sum$ local distances



EXEMPLAR

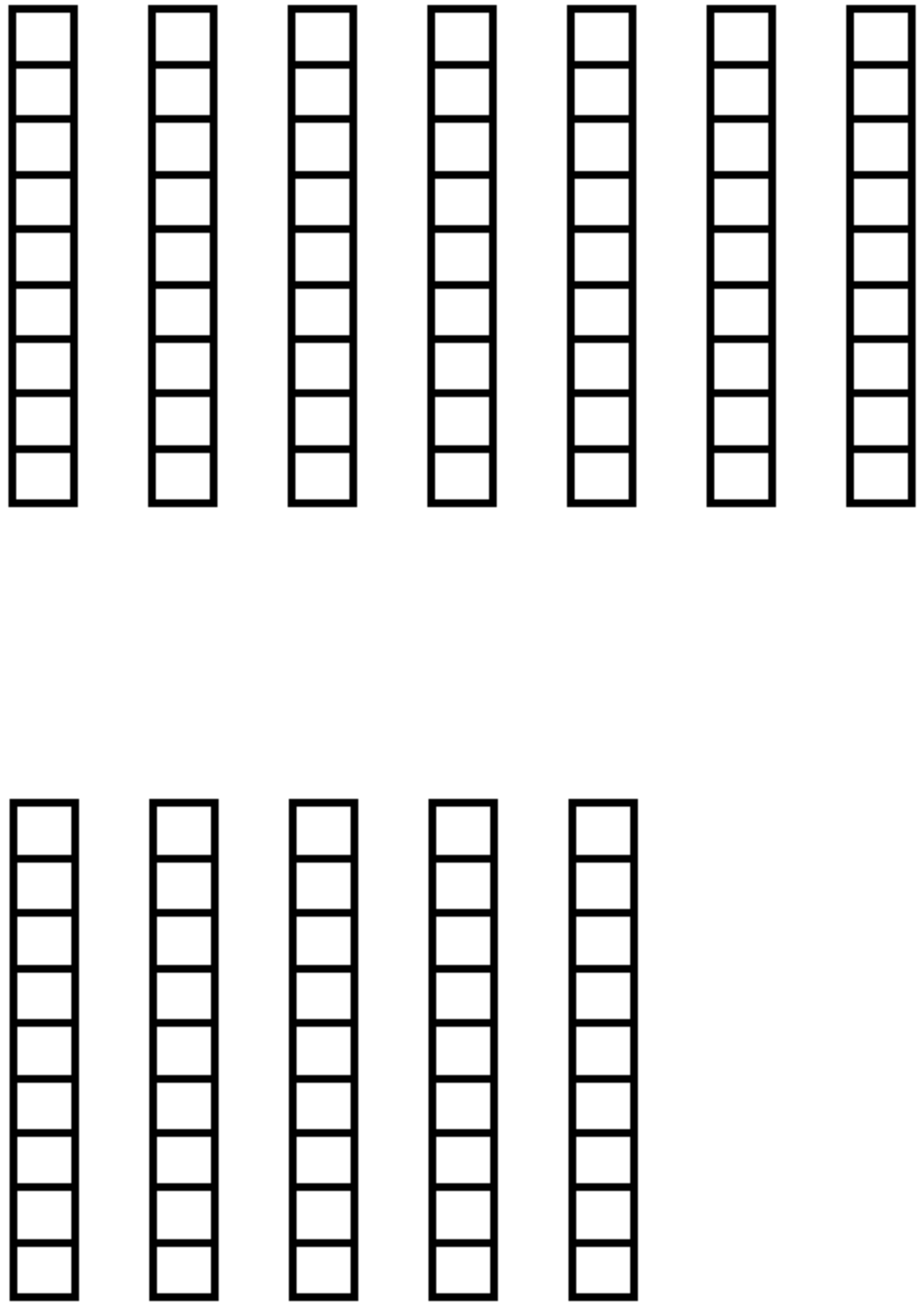
Image credit: Figure 8.1 from Holmes & Holmes


FEATURES
FEATURE VECTOR
FILTERBANK
MEL SCALE
COCHLEA
SEQUENCE OF FEATURE VECTORS
SEQUENCE
EXEMPLAR
DISTANCE
DYNAMIC PROGRAMMING (DTW)

Pattern matching by Dynamic Time Warping

template

unknown



1,1	1,1	1,1
2,2	2,2	2,1
3,3	3,2	3,2
4,3	**4,3**	**4,3**
5,?	5,?	5,?
6,?	6,?	6,?
7,?	7,?	7,?

Dynamic Time Warping is a form of Dynamic Programming

- Understanding Dynamic Programming, as an algorithm

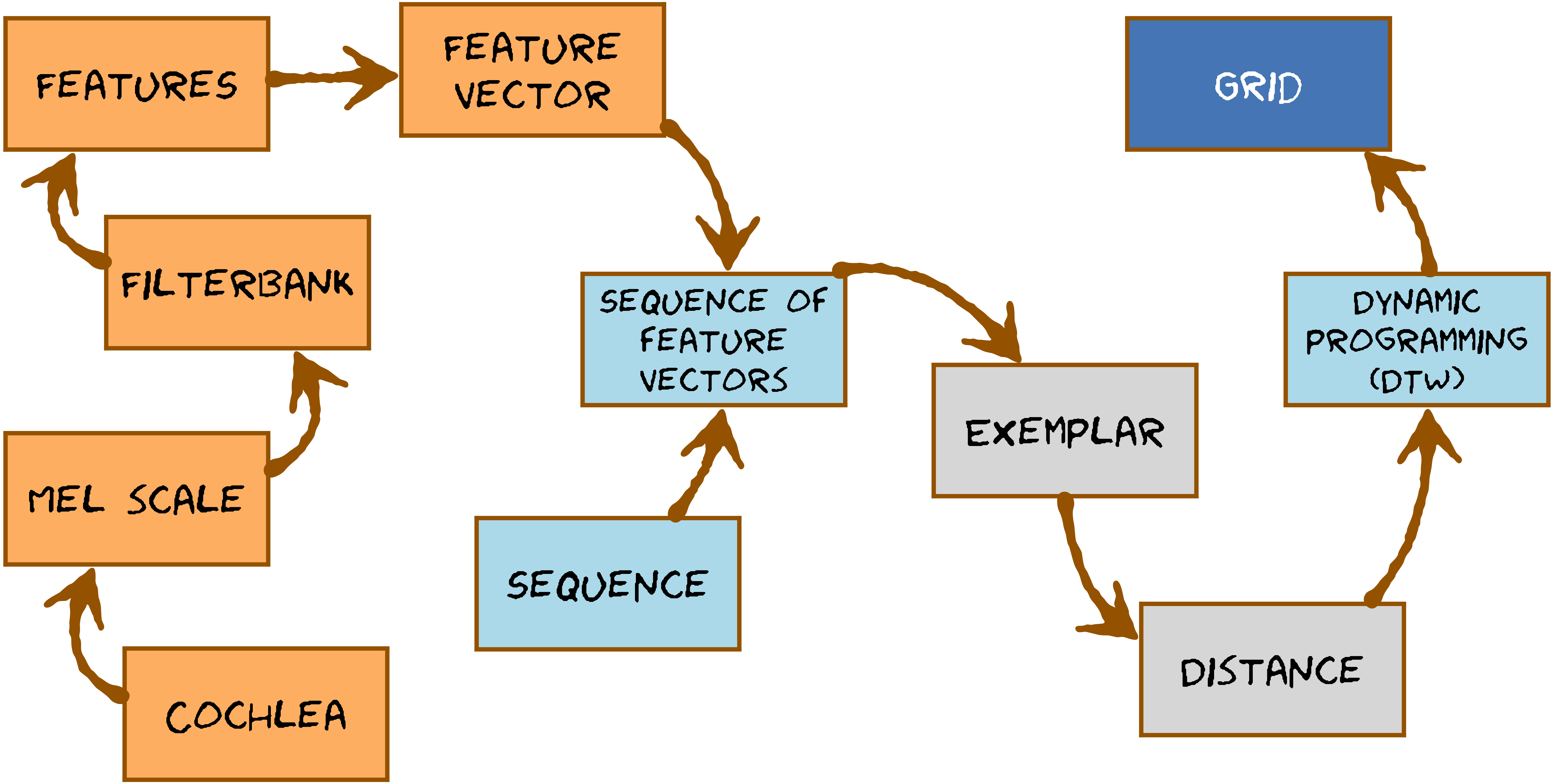
Getting harder

- Being able to see that Dynamic Programming can be applied to a particular problem

Really quite difficult

- Devising a suitable data structure for that problem

My brain hurts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FEATURE VECTOR
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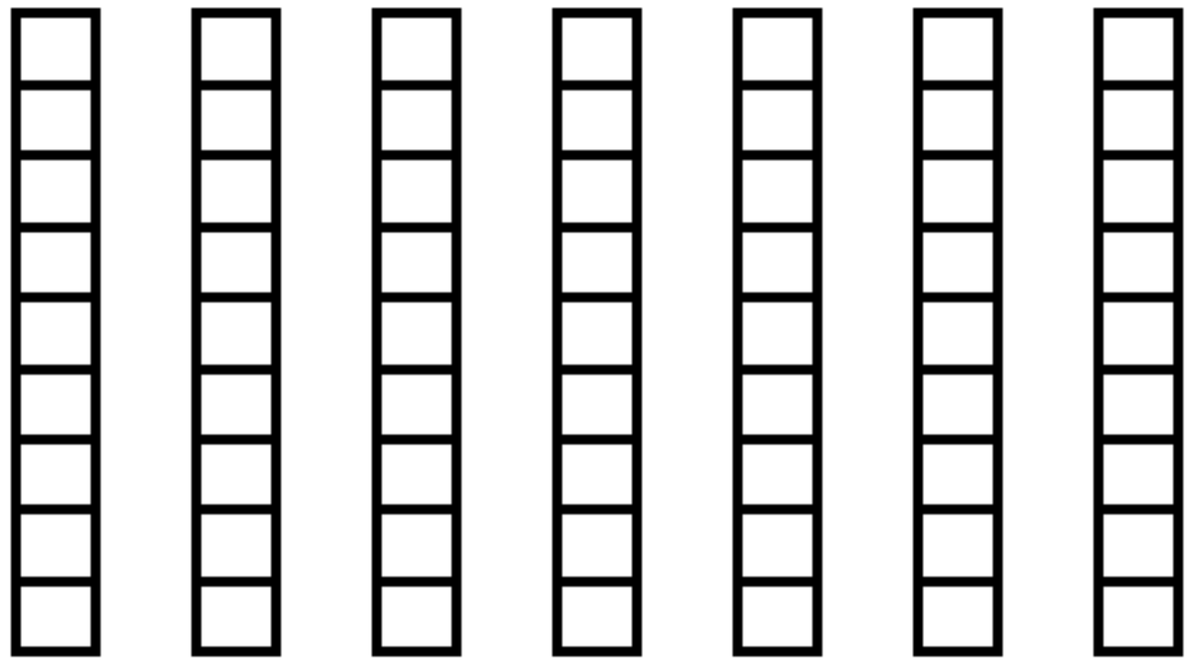
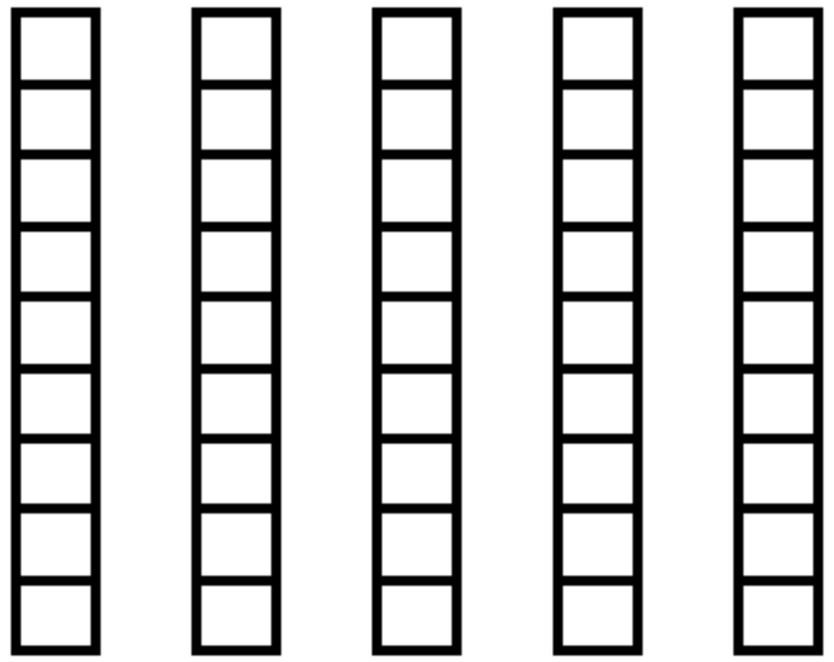
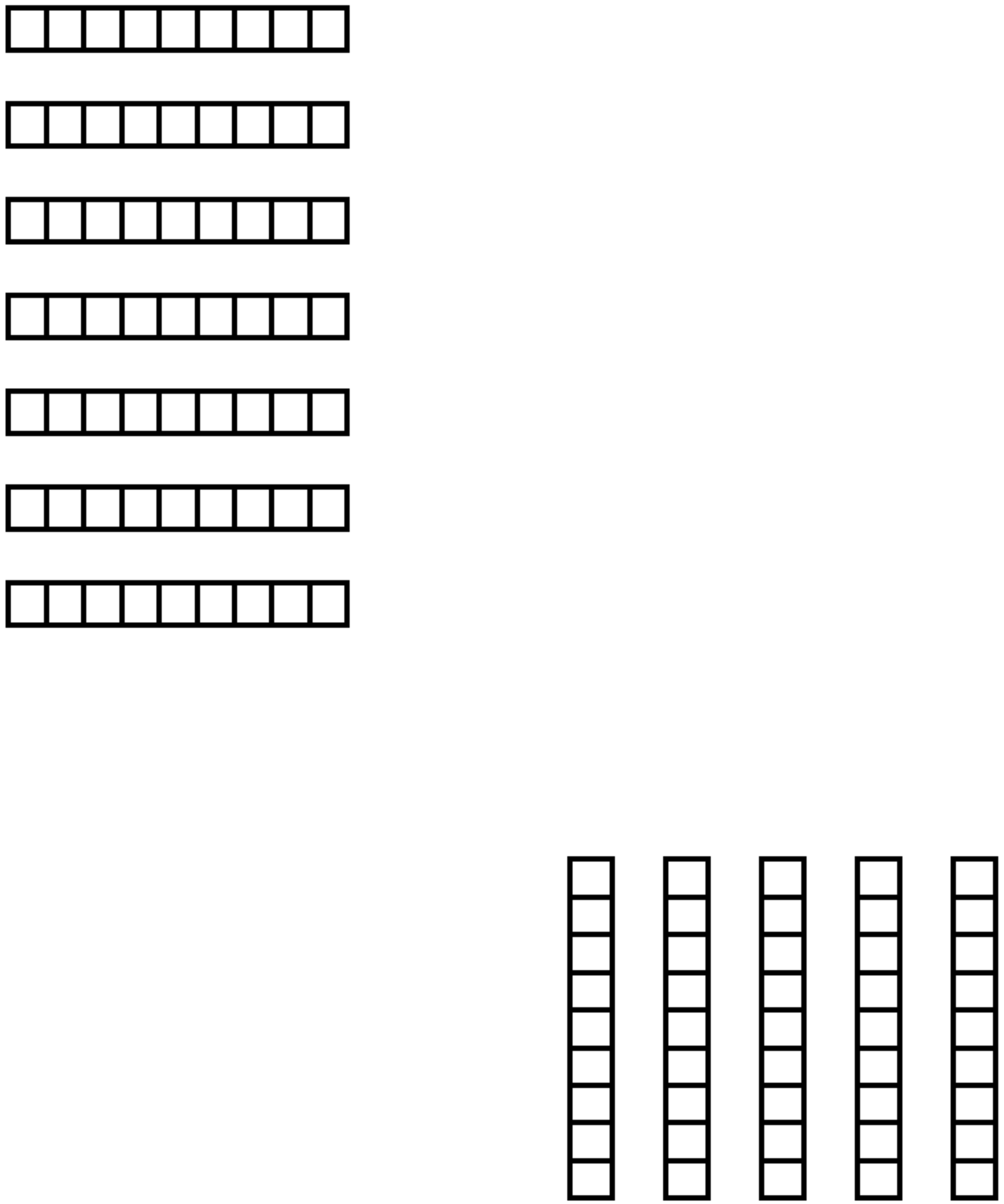
FILTERBANK
SEQUENCE OF FEATURE VECTORS
DYNAMIC PROGRAMMING (DTW)
EXEMPLAR
MEL SCALE
SEQUENCE
DISTANCE
COCHLEA

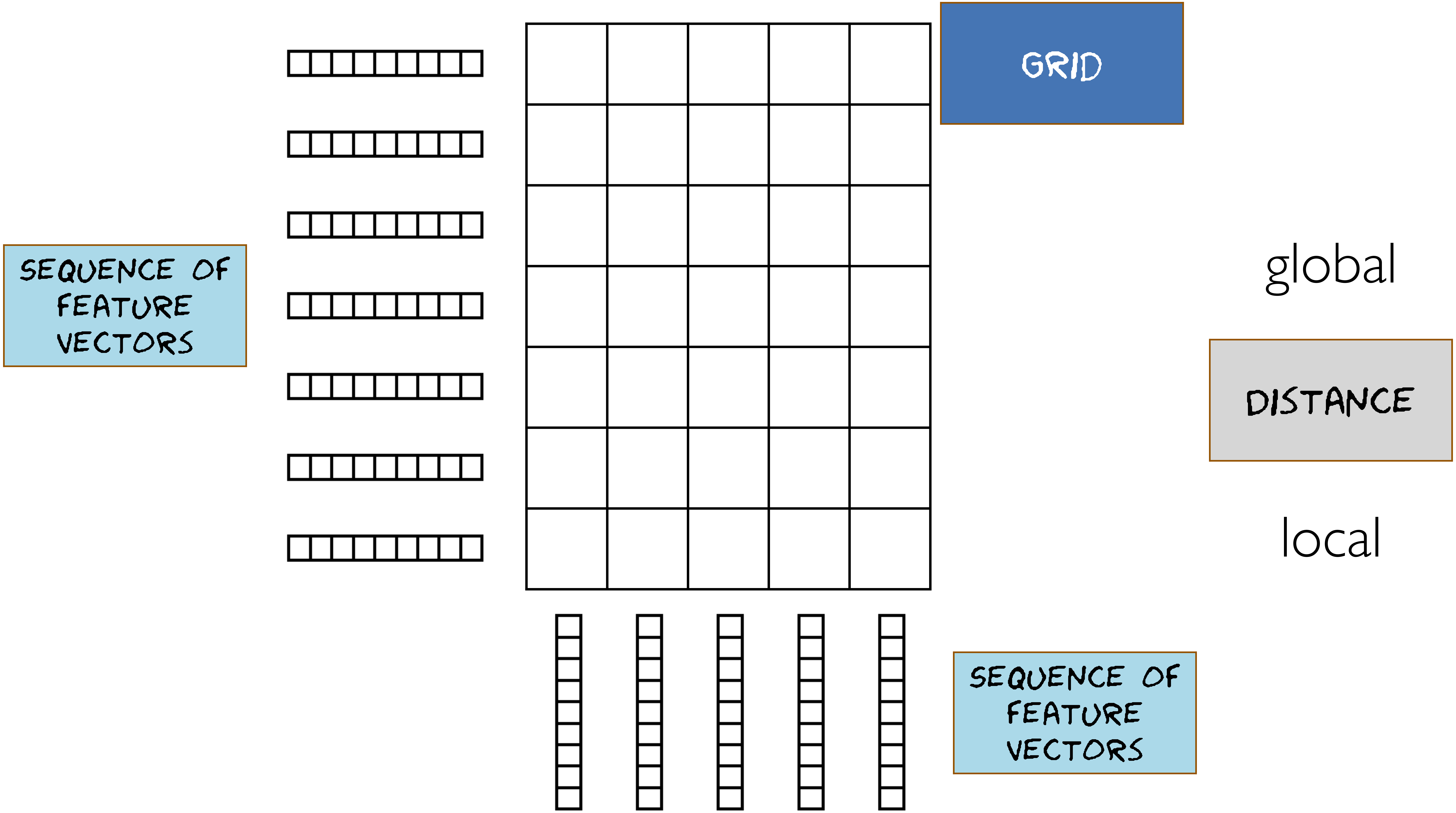
‘‘three’’





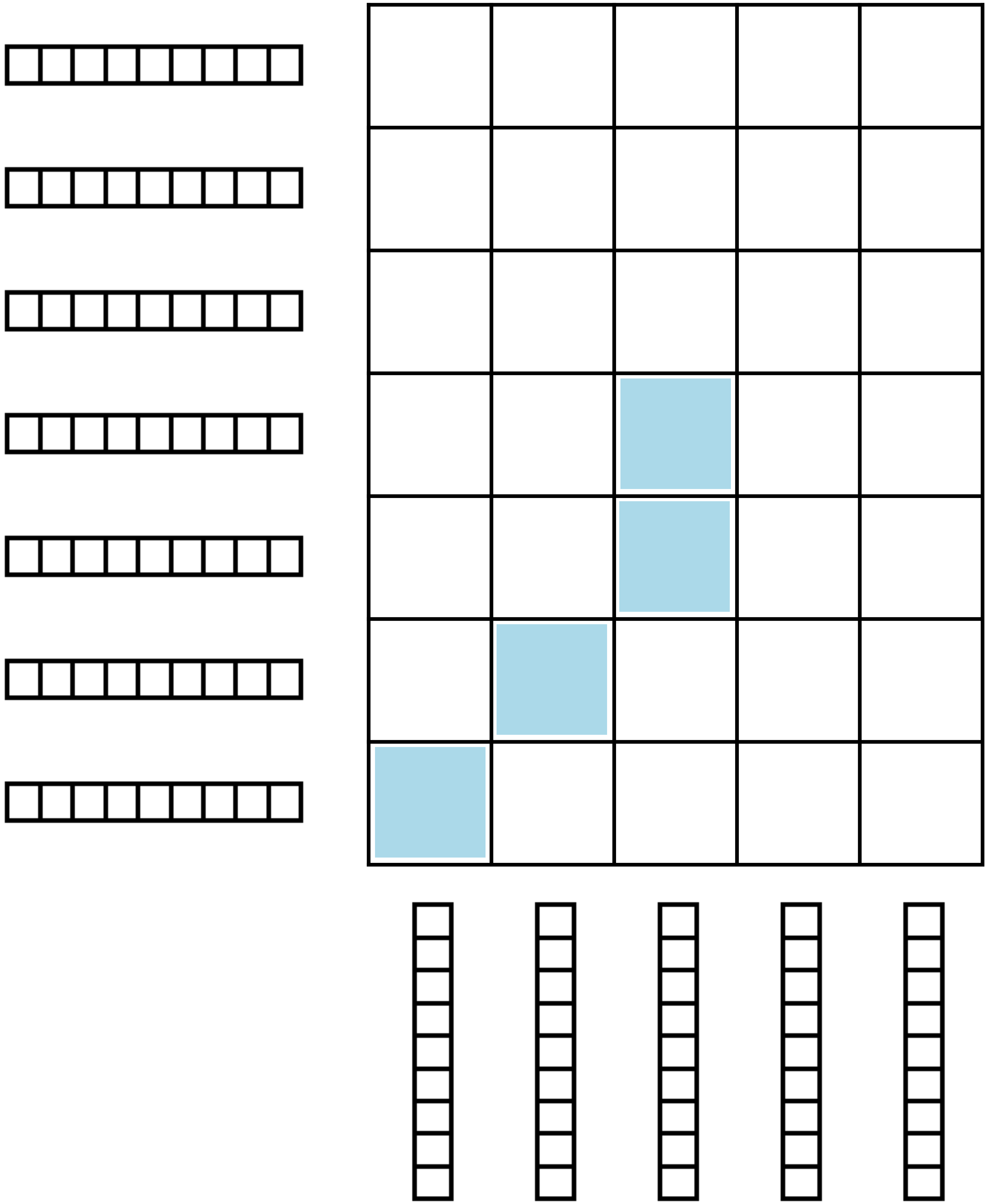
‘‘???’’





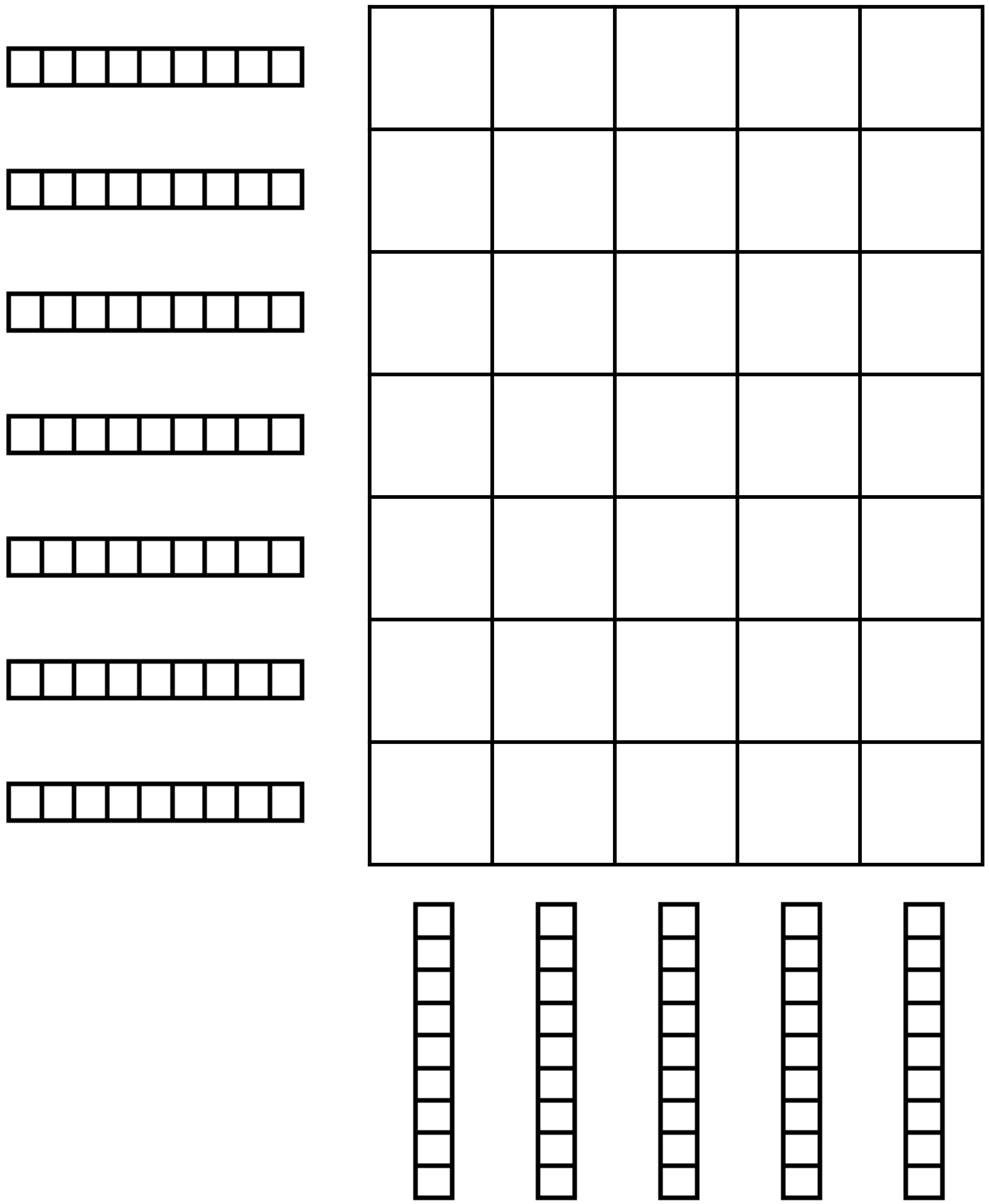
GRID
SEQUENCE OF FEATURE VECTORS
global
DISTANCE
local
SEQUENCE OF FEATURE VECTORS

DYNAMIC PROGRAMMING (DTW)

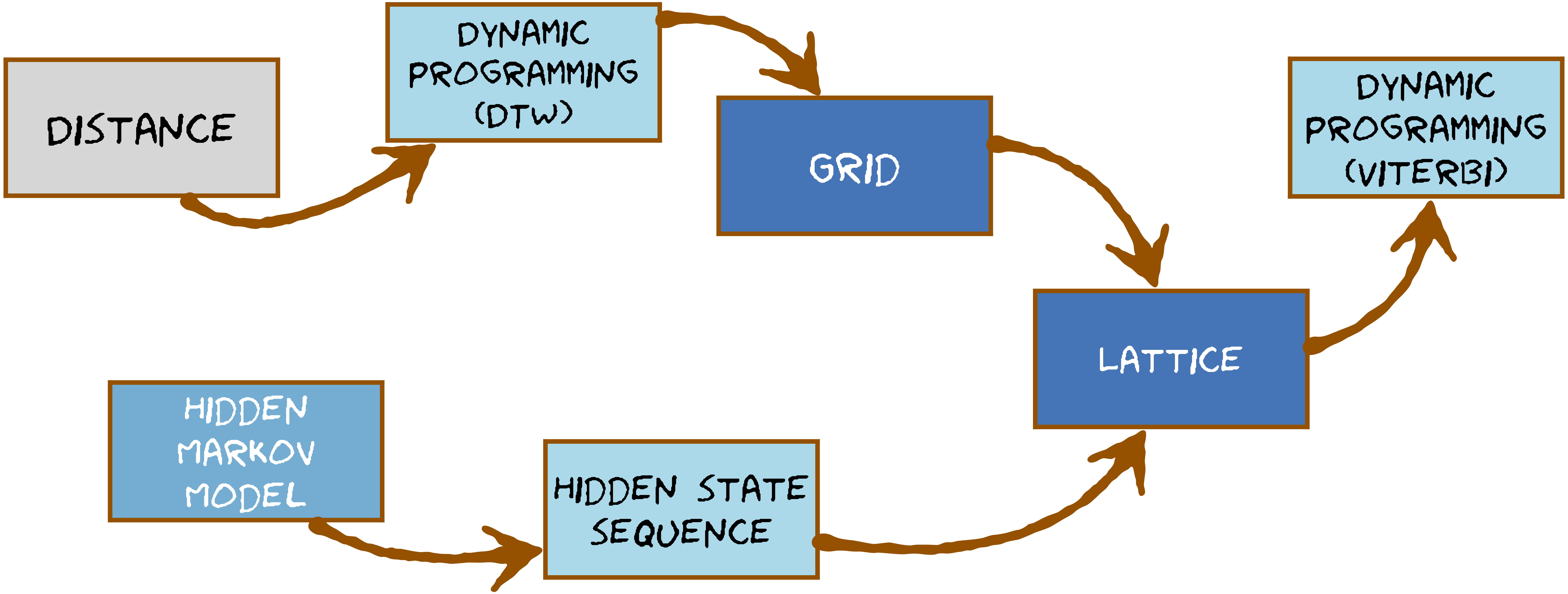


1 , 1
2 , 2
3 , 3
4 , 3
5 , ?
6 , ?
7 , ?

DYNAMIC PROGRAMMING (DTW)



What you can learn next



What next?

- DTW, and especially the local distance measure doesn't account for **variability**
  - so we'll replace it with a **probabilistic model**

HMMs in Module 8

- That model will use Gaussian probability density functions
  - to make these simpler, we will first try to remove covariance from our **features**
  - time for some **feature engineering** !

MFCCs in Module 7