# Speech Processing

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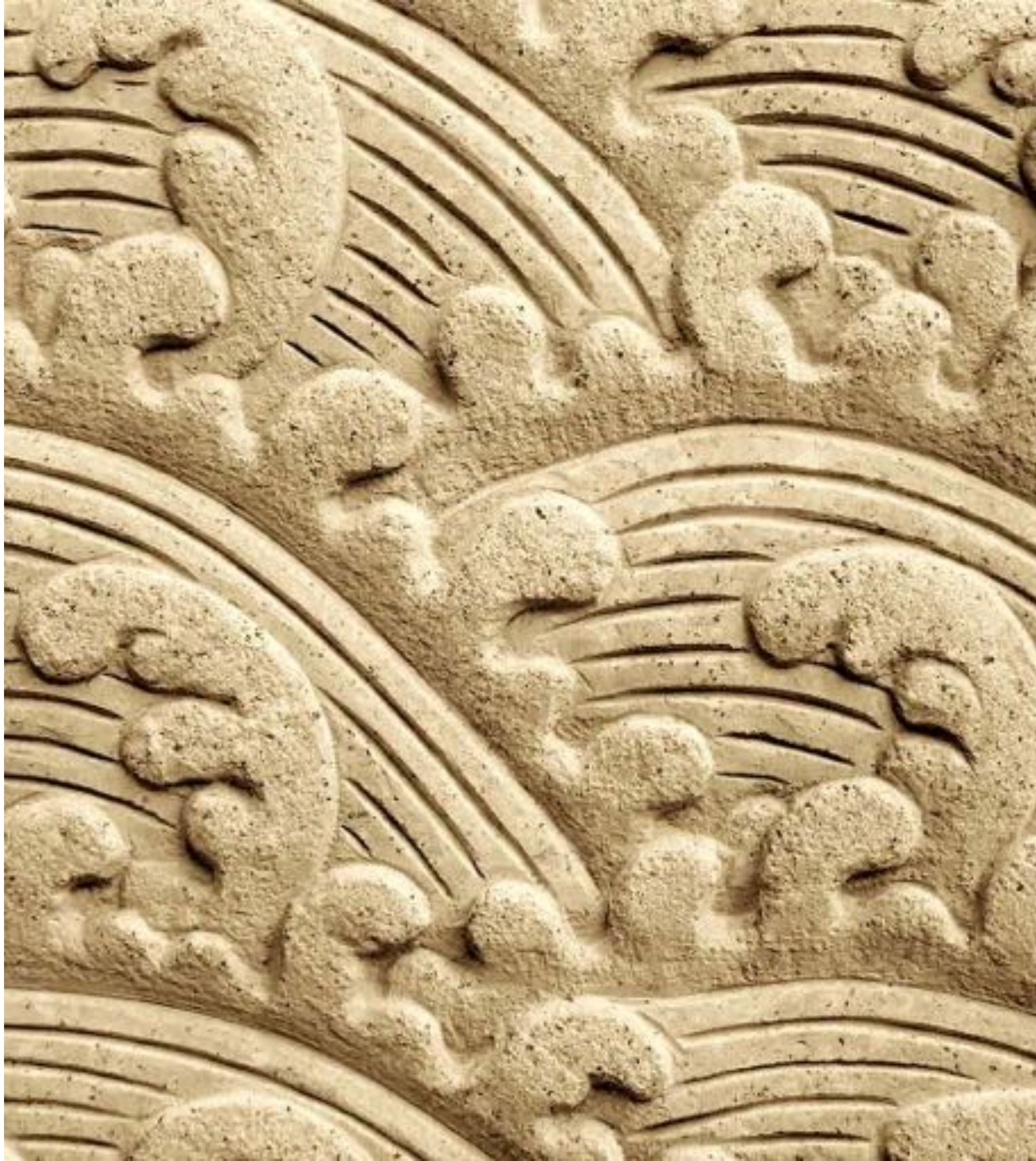
University of Edinburgh

2022-23



# Module 7

## 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**

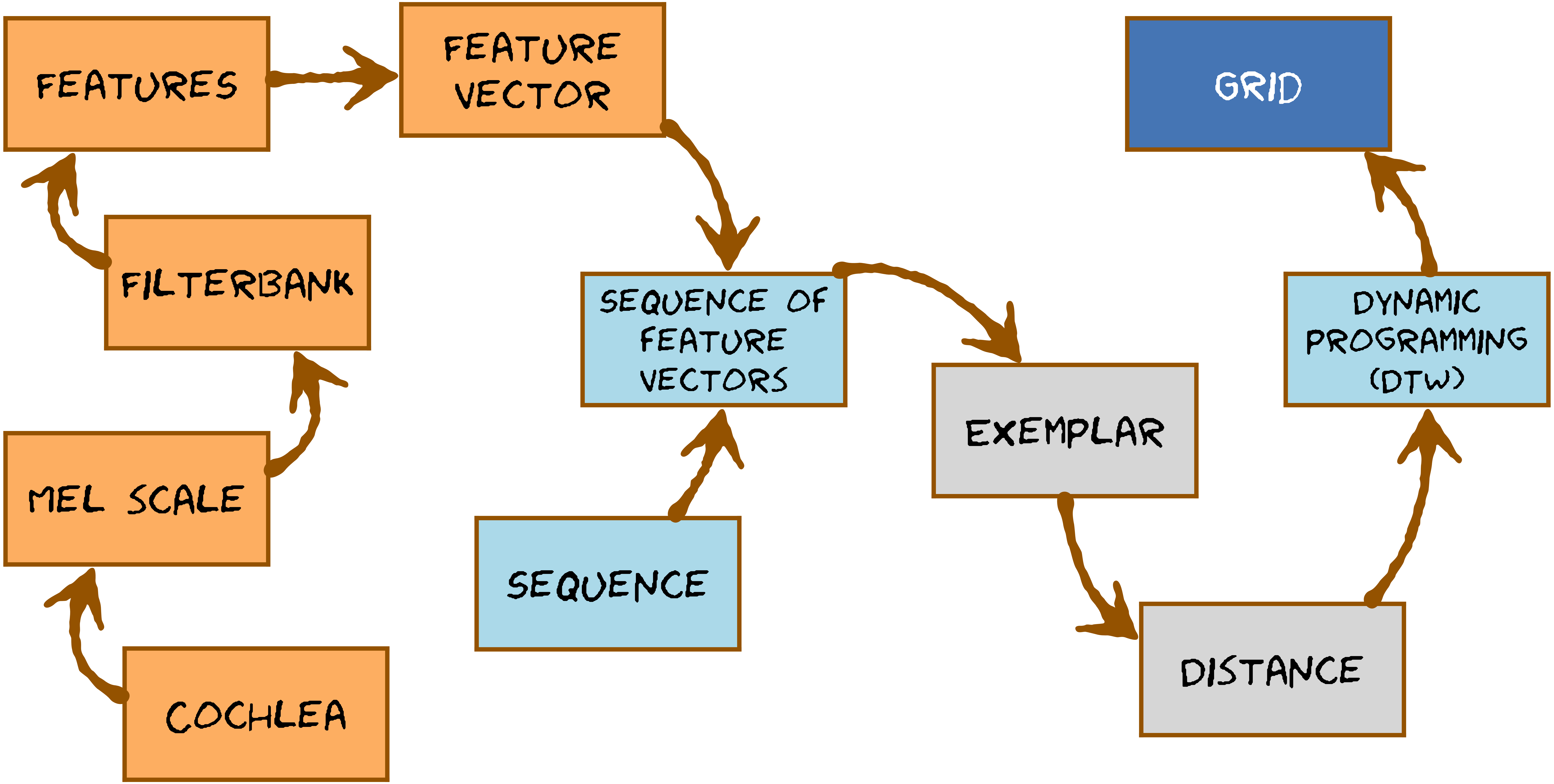
Speech waveforms change over time

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

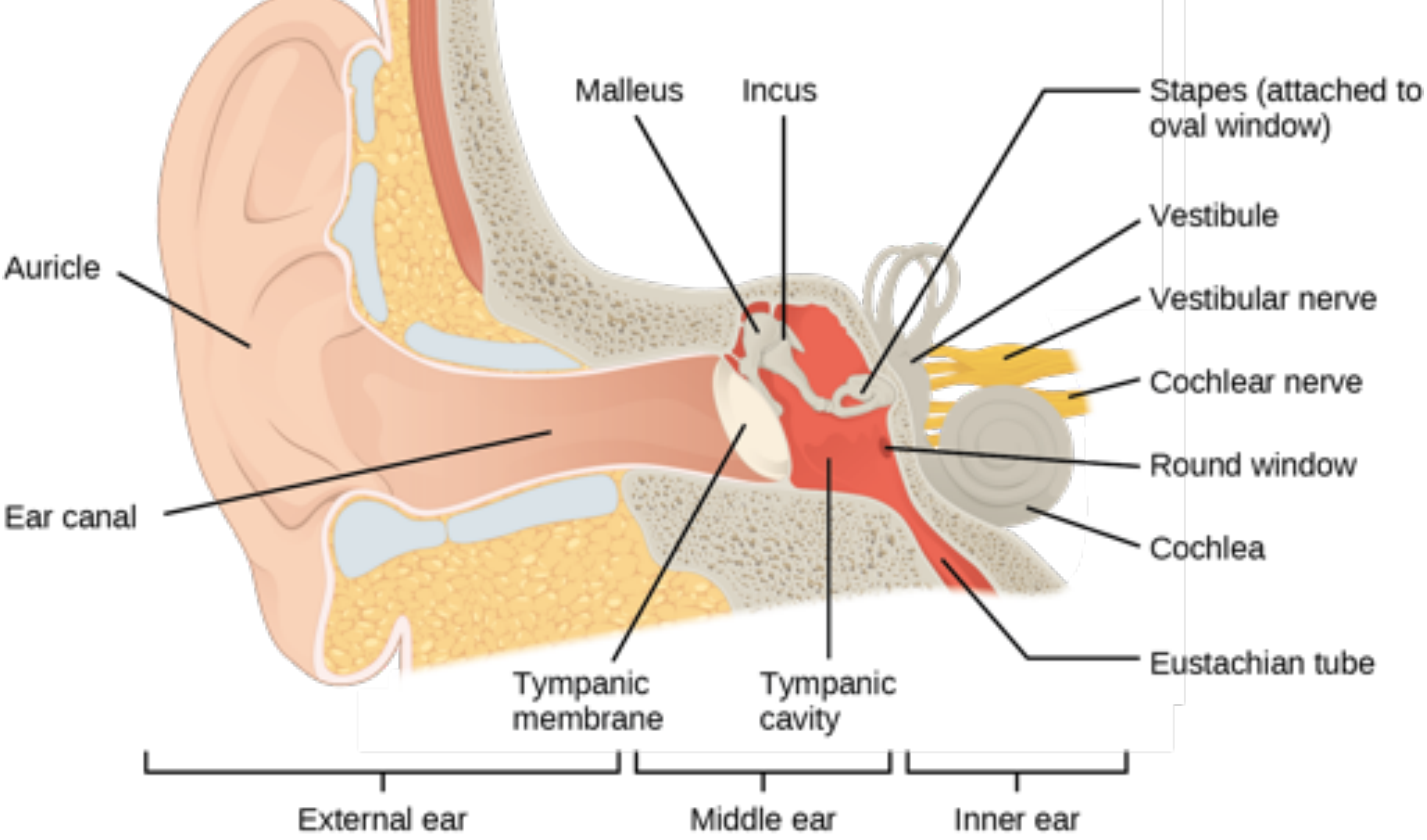
MEL SCALE

SEQUENCE

DISTANCE

COCHLEA

COCHLEA



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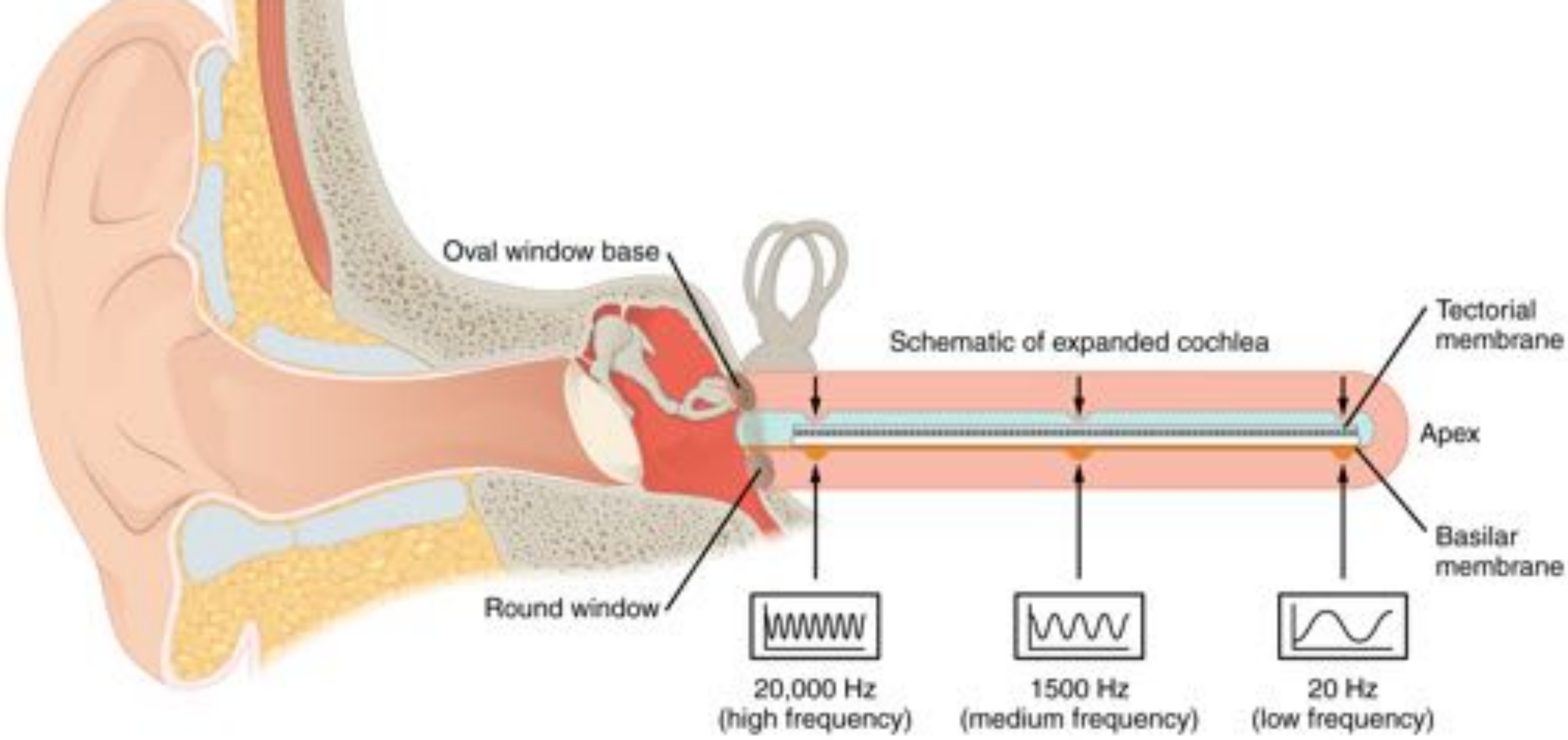

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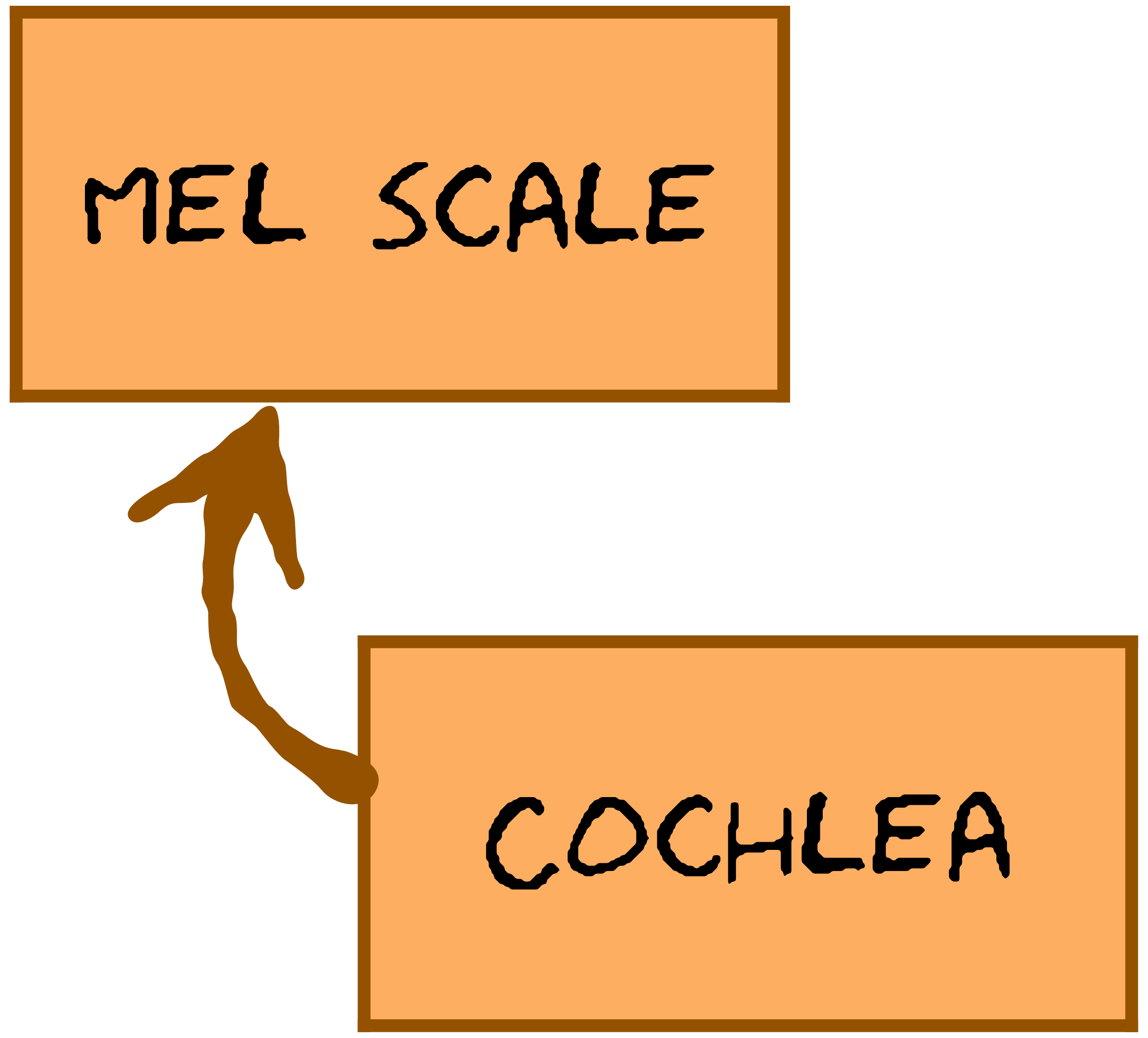
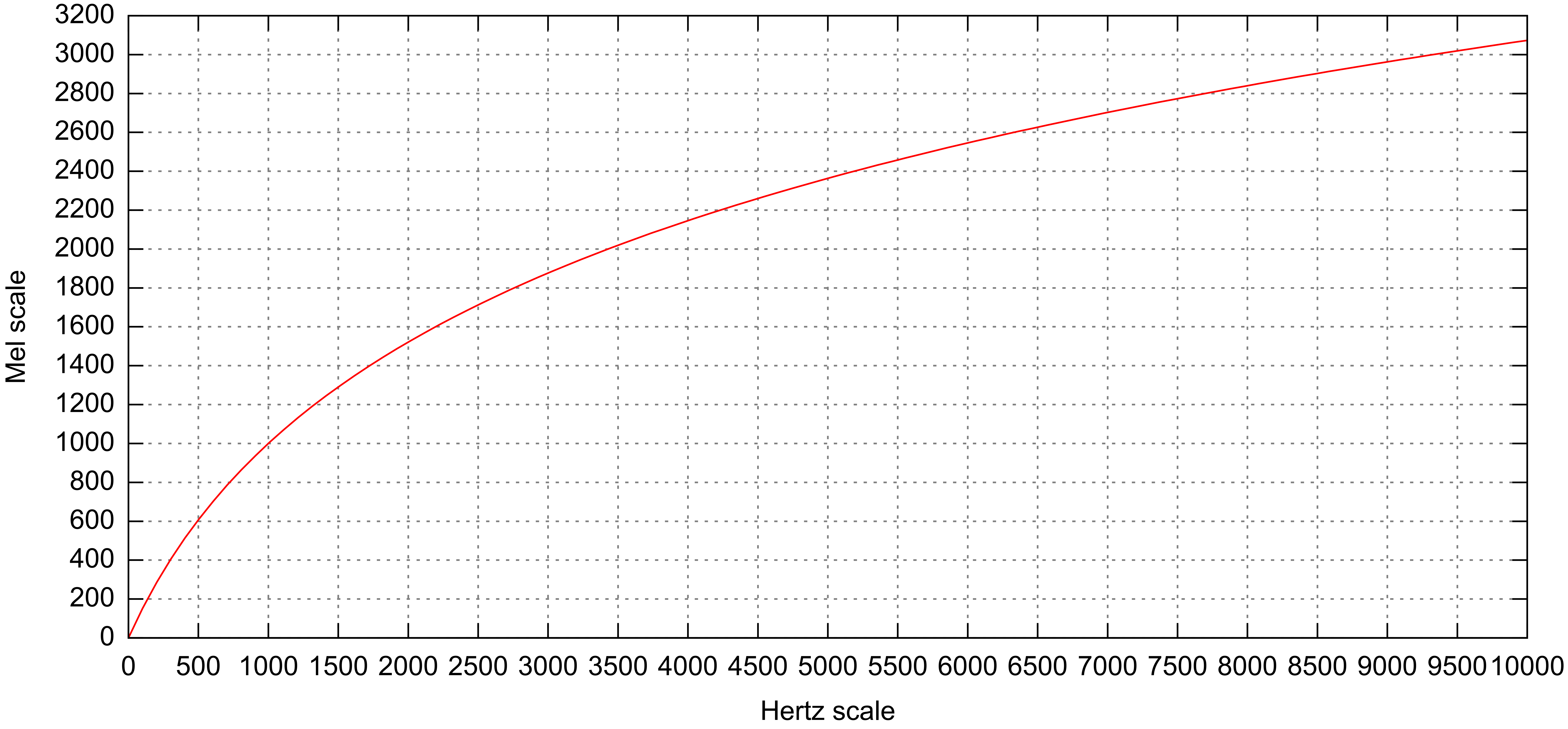
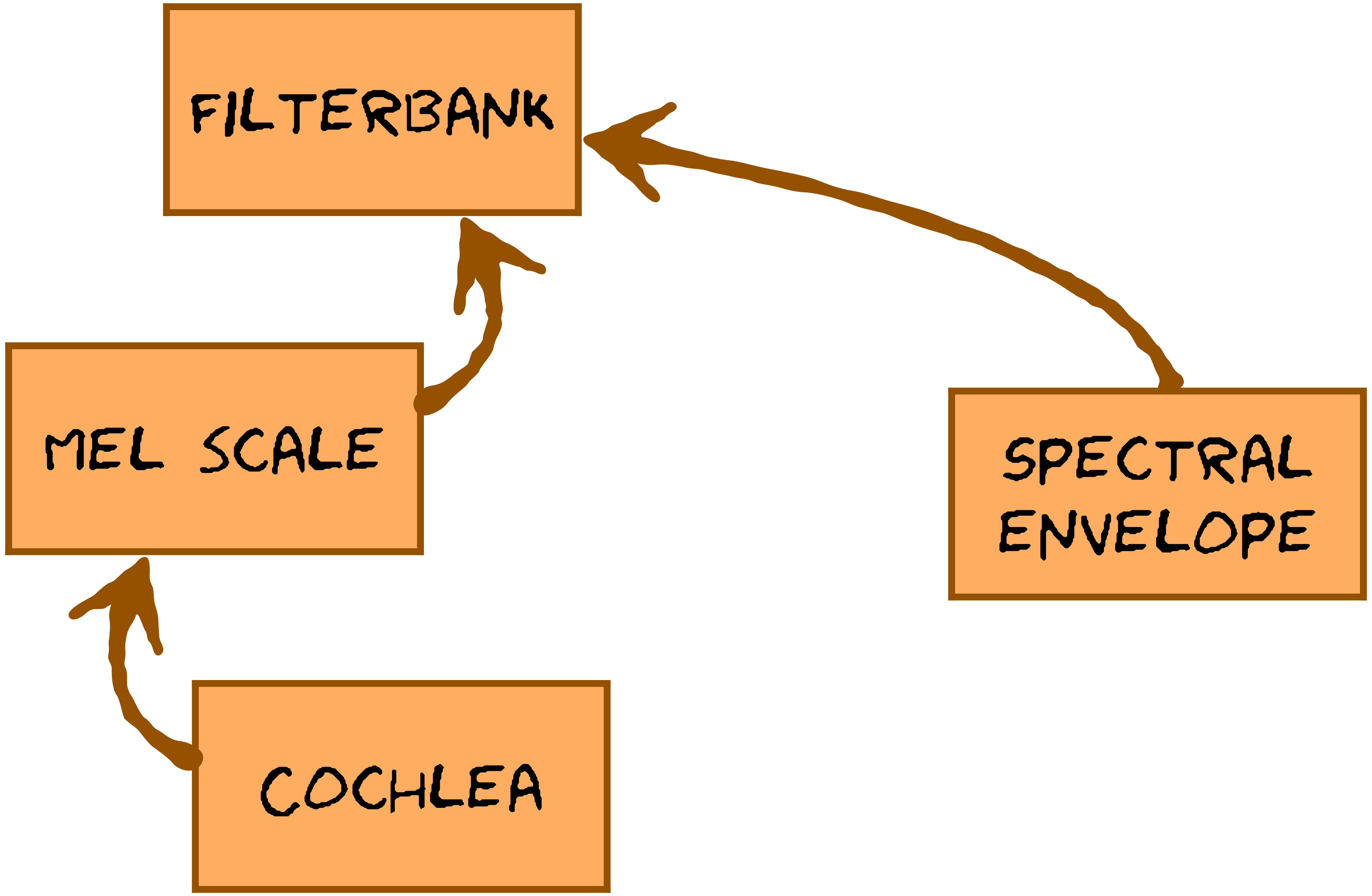


MEL SCALE

COCHLEA


3200
3000
2800
2600
2400
2200
2000
1800
1600
1400
1200
1000
800
600
400
200
0
Mel scale
0
500
1000
1500
2000
2500
3000
3500
4000
4500
5000
5500
6000
6500
7000
7500
8000
8500
9000
9500
10000
Hertz scale



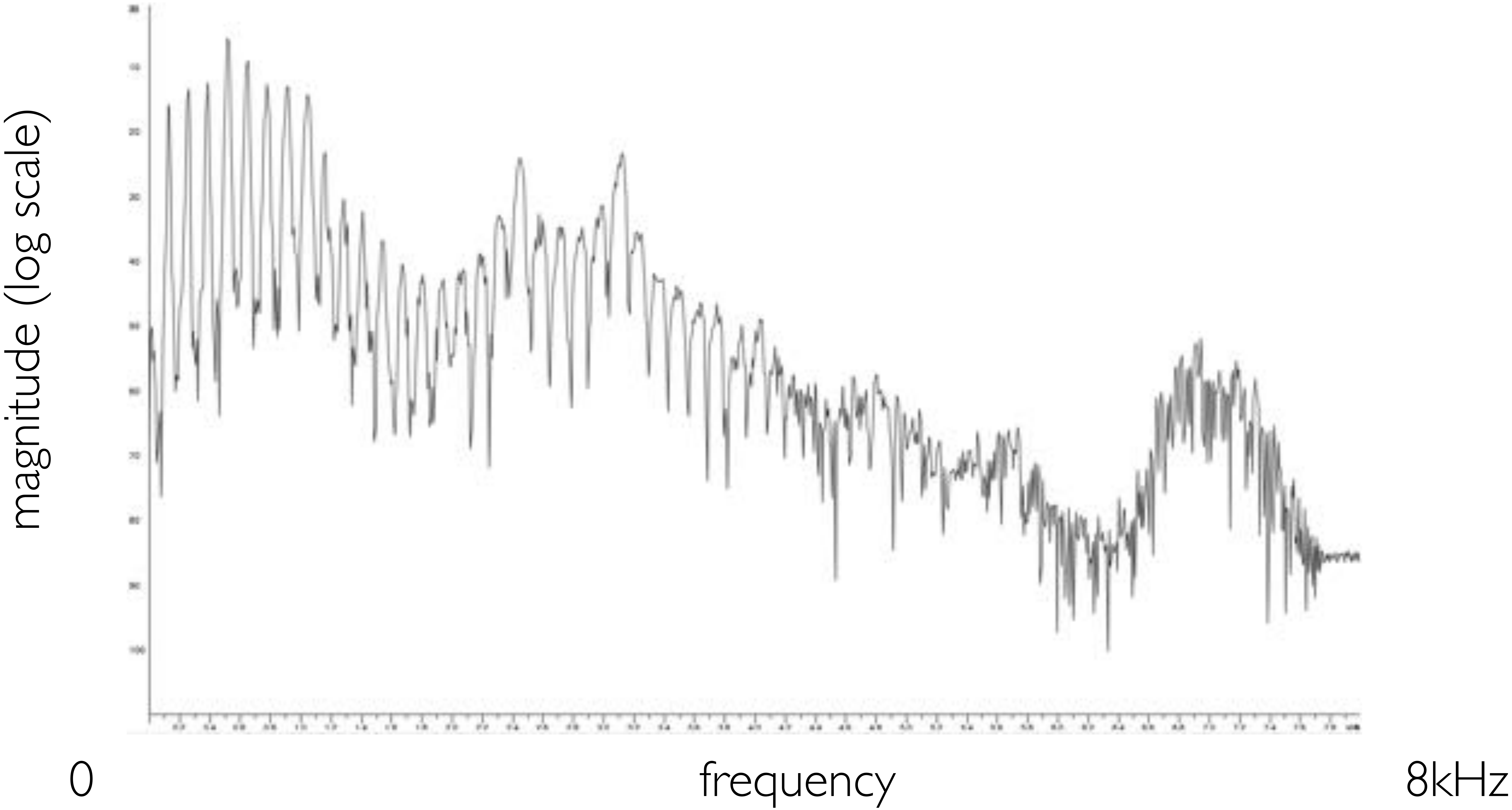
FILTERBANK

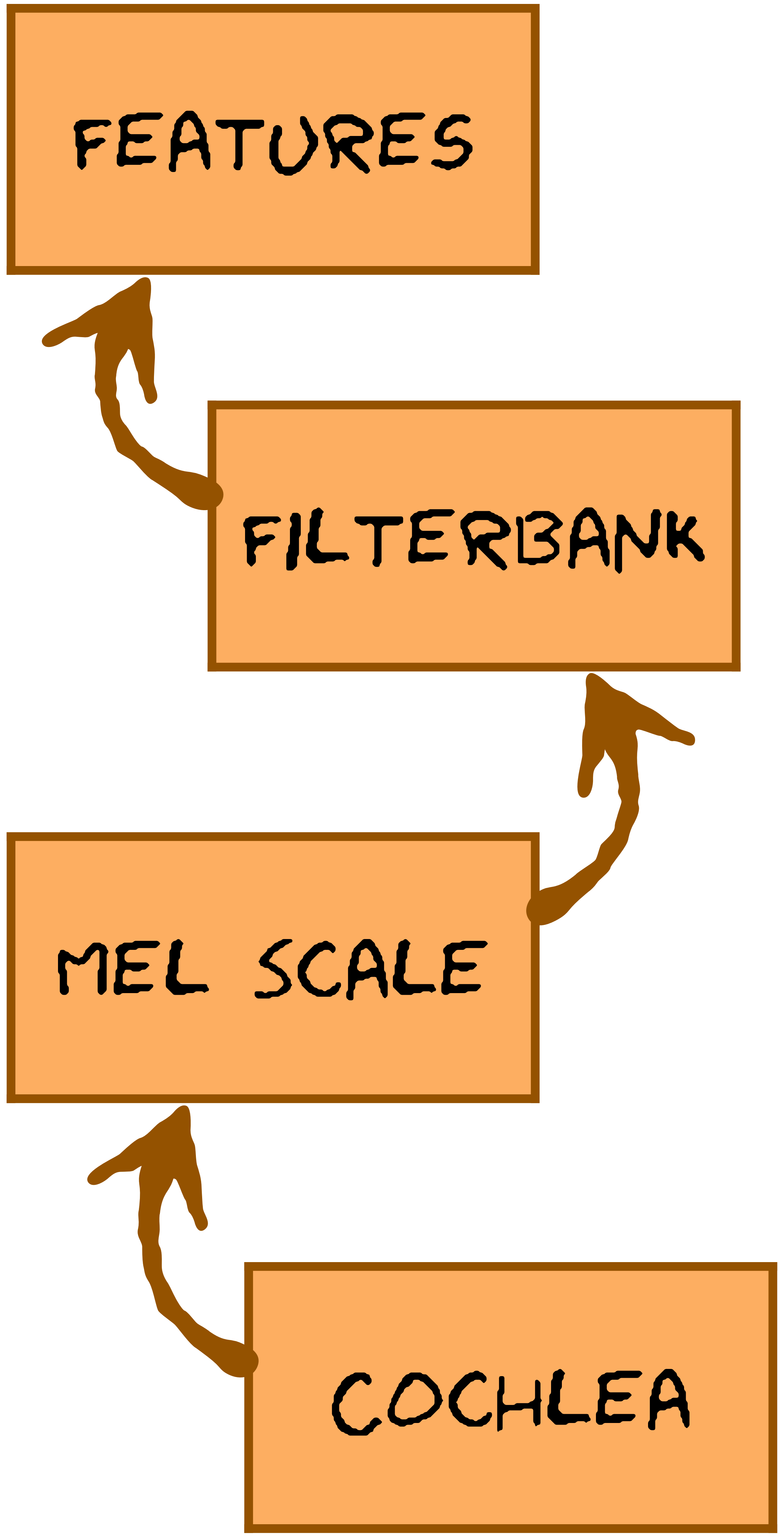
MEL SCALE

SPECTRAL ENVELOPE

COCHLEA

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





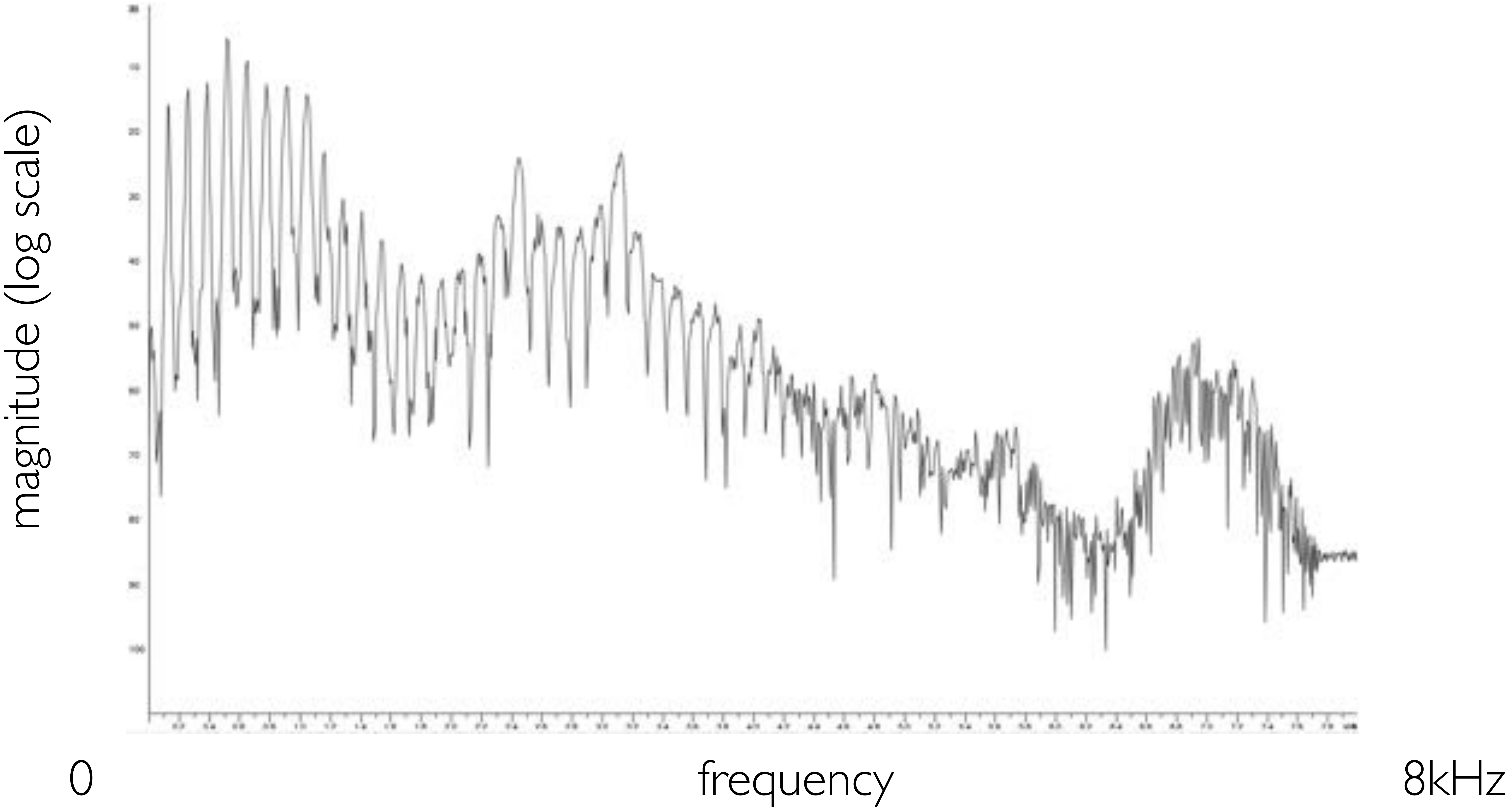
FEATURES

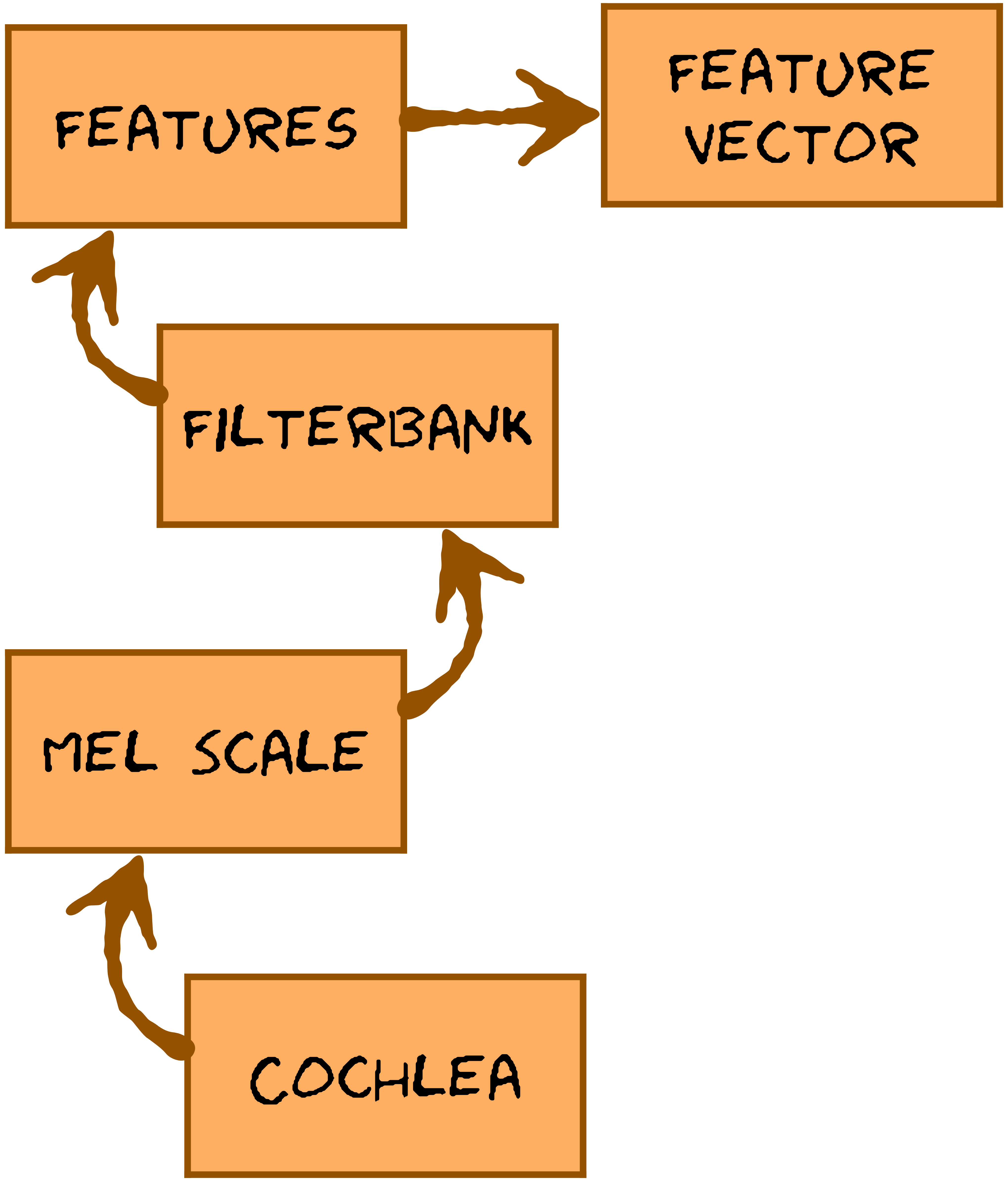
FILTERBANK

MEL SCALE

COCHLEA

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





FEATURES

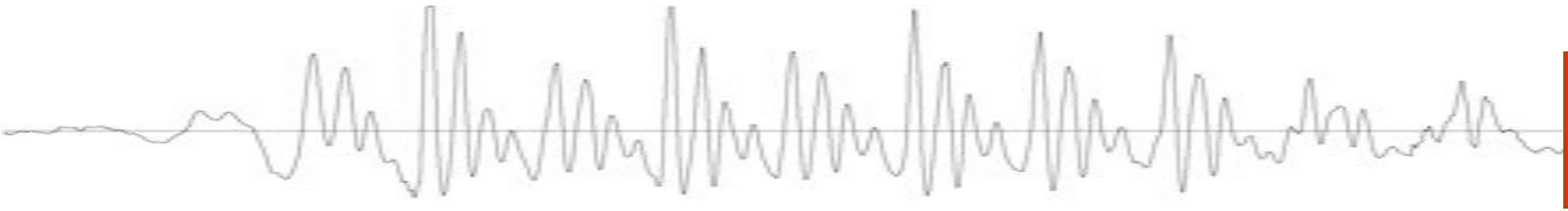
FEATURE VECTOR

FILTERBANK

MEL SCALE

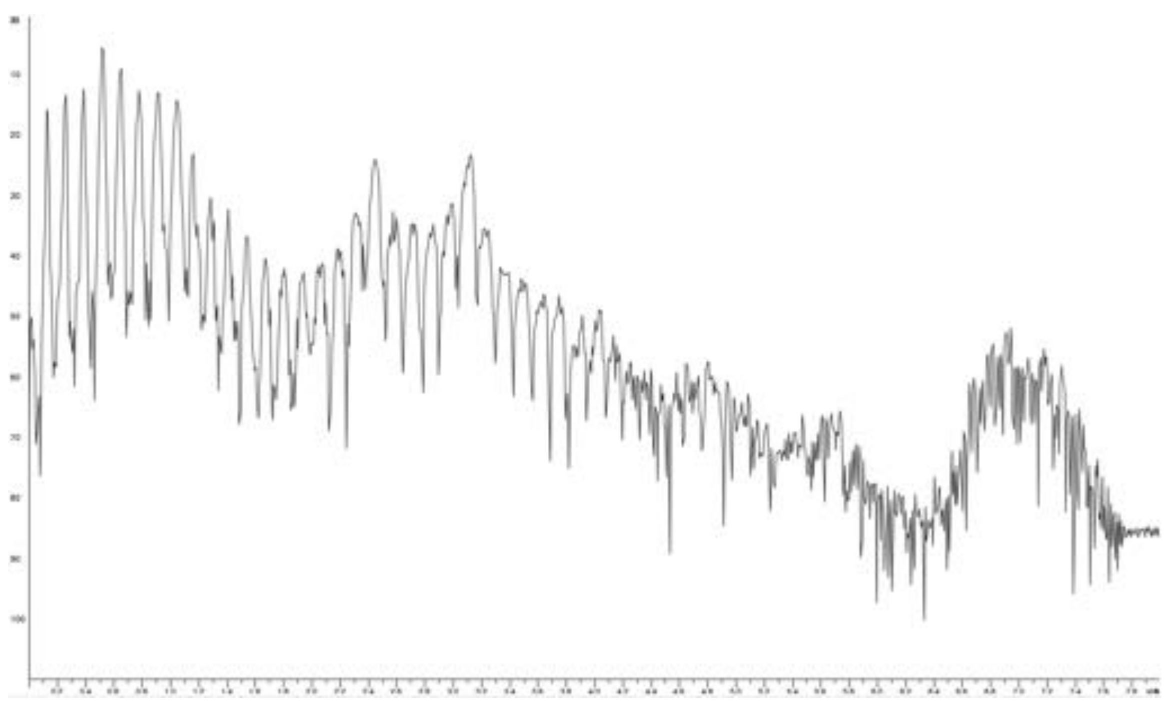
COCHLEA

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

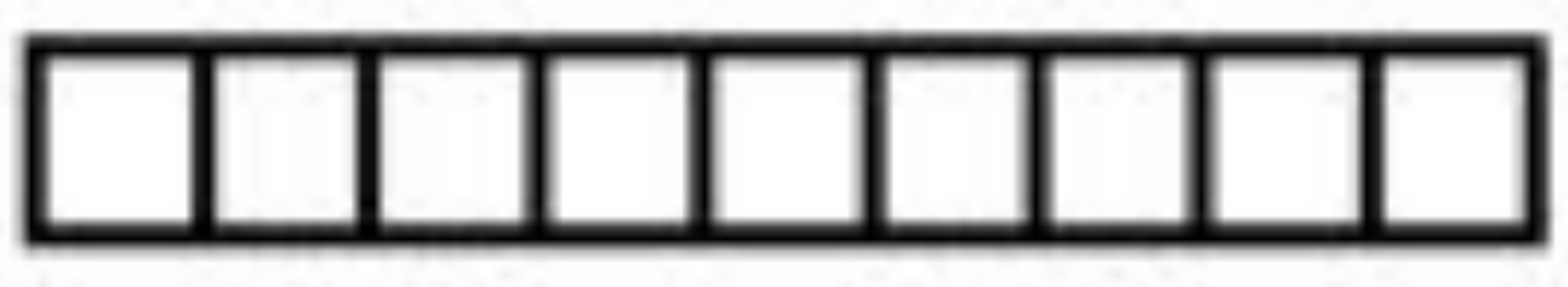


TIME DOMAIN

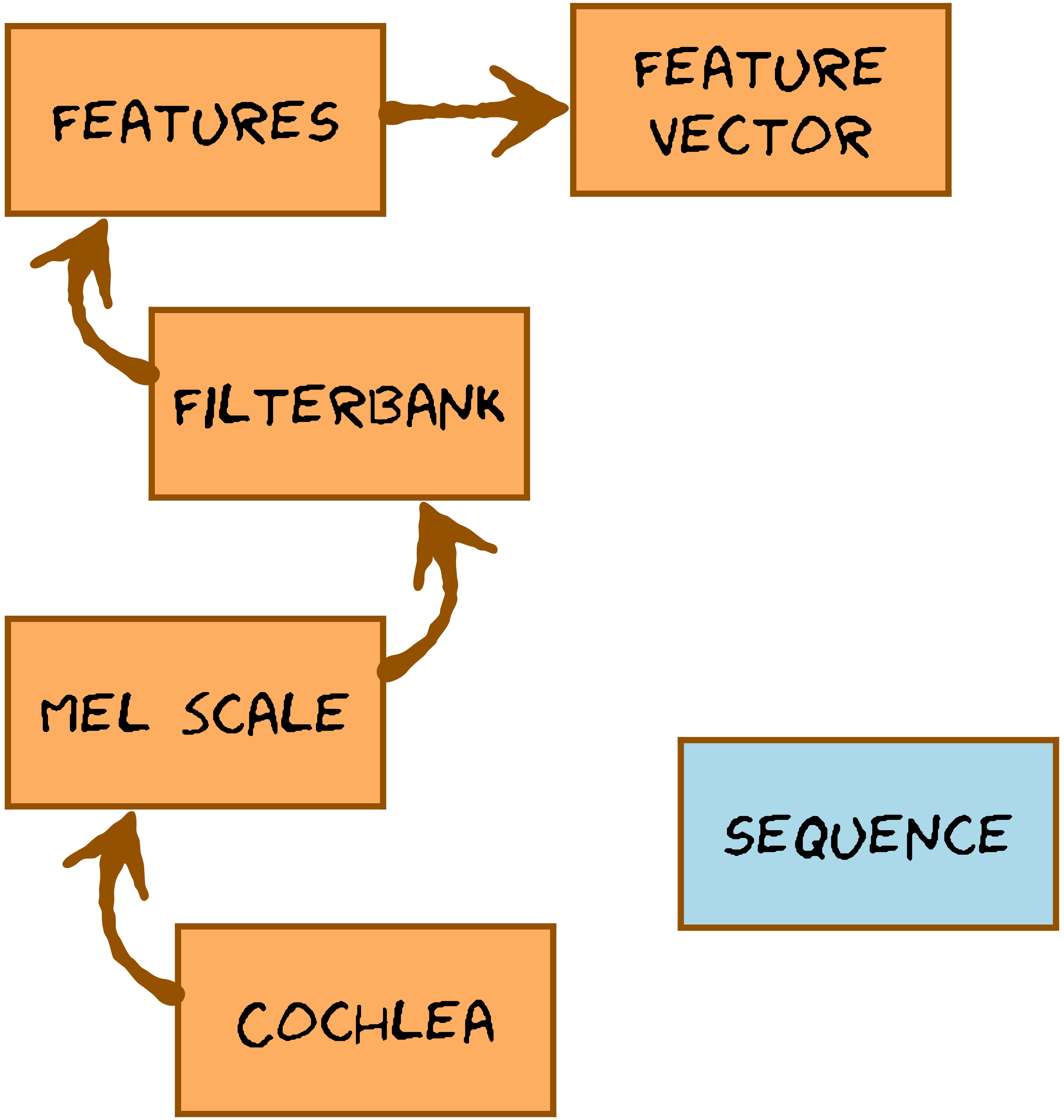
FEATURES



FREQUENCY DOMAIN



FEATURE VECTOR



FEATURES

FEATURE VECTOR

FILTERBANK

MEL SCALE

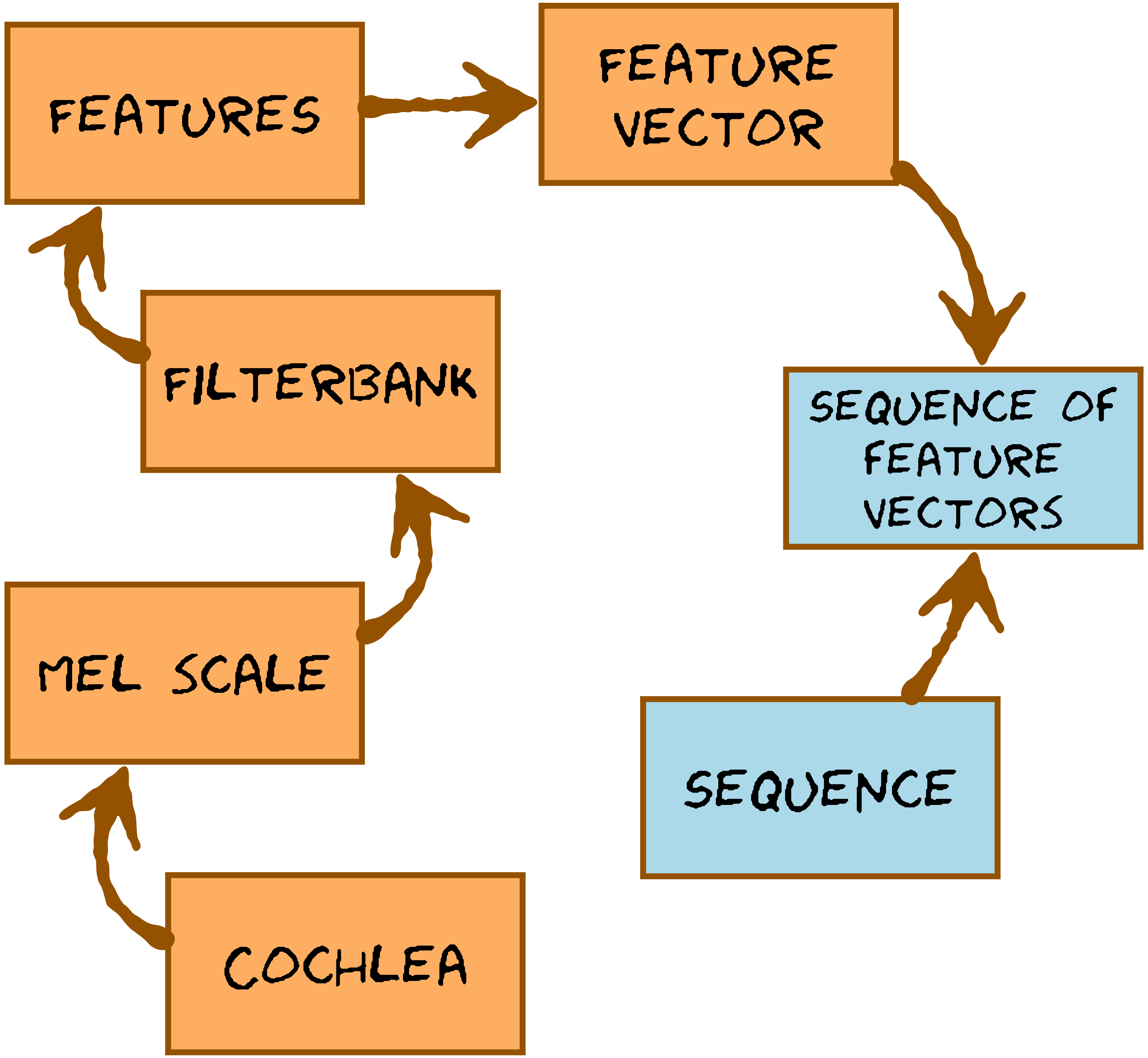
COCHLEA

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**



FEATURES

FEATURE VECTOR

FILTERBANK

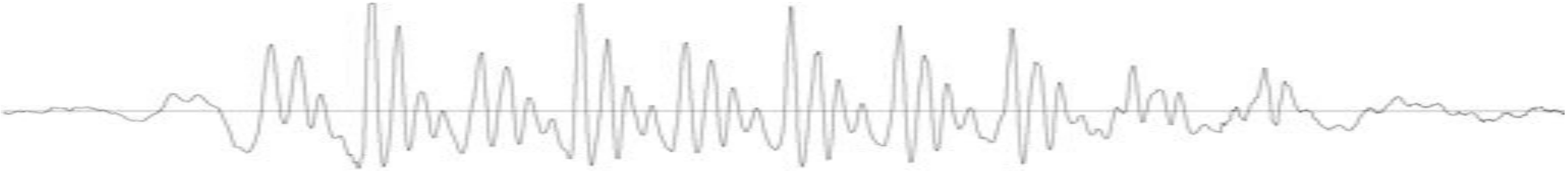
SEQUENCE OF FEATURE VECTORS

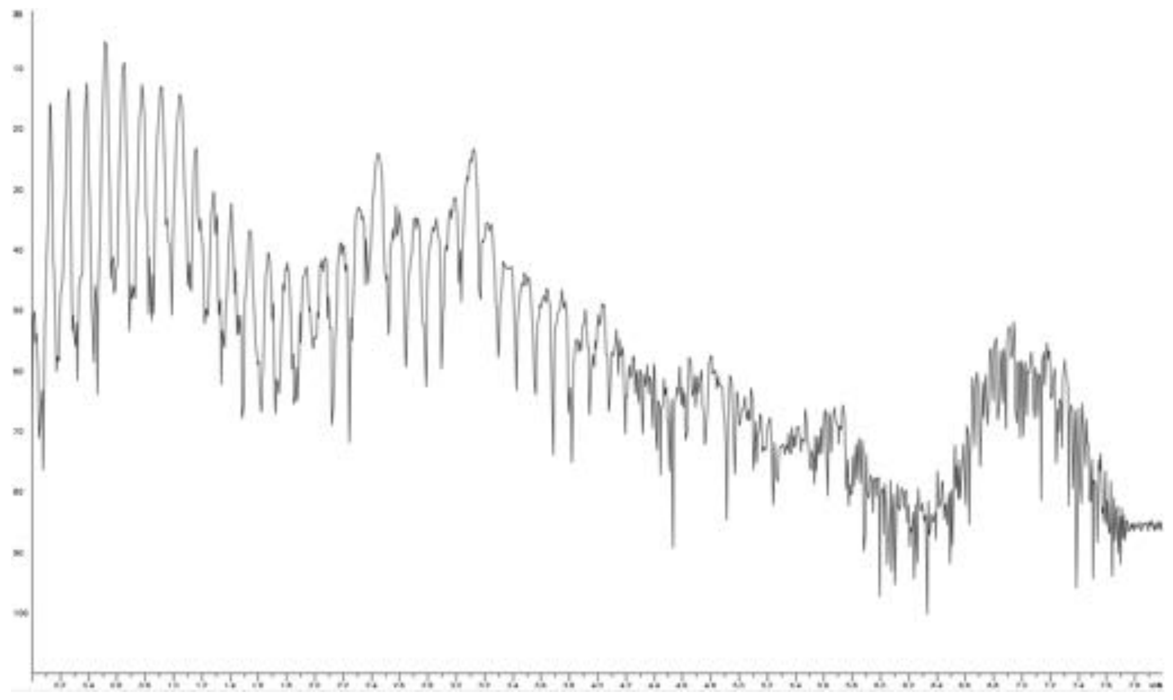
MEL SCALE

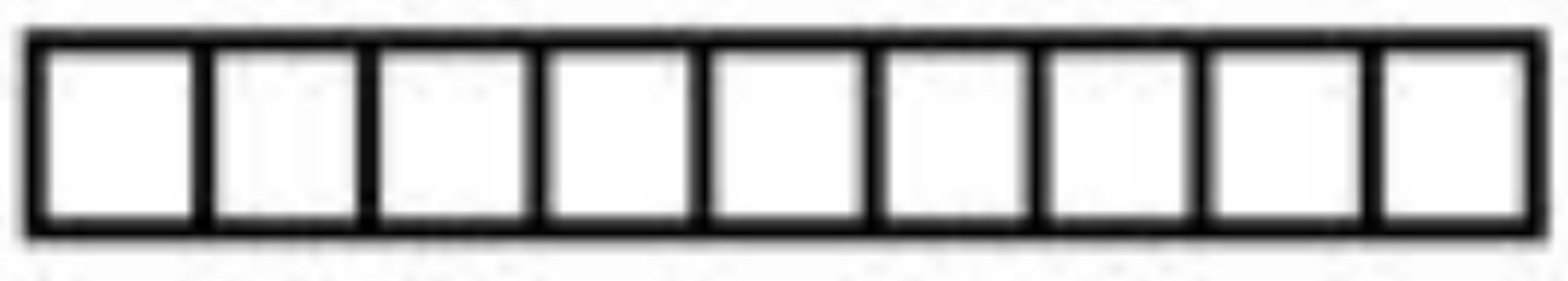
SEQUENCE

COCHLEA

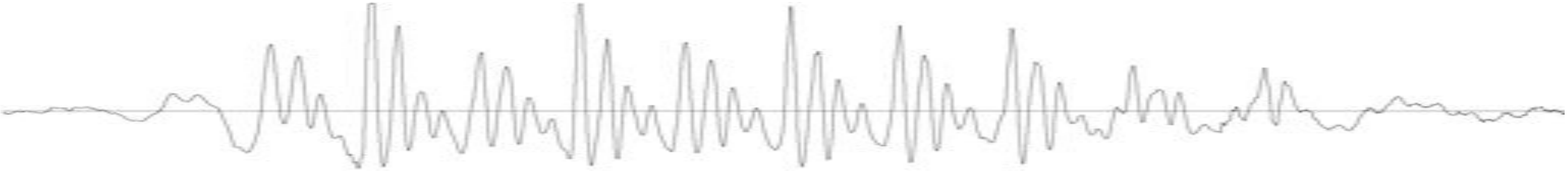
# Filterbank features for one frame are speech are stored in a single vector

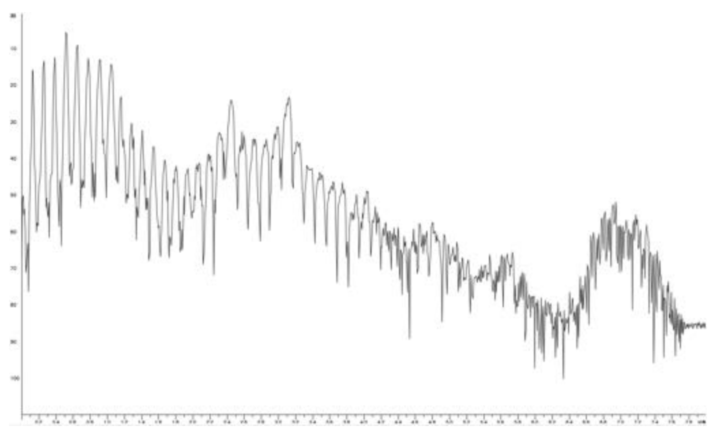






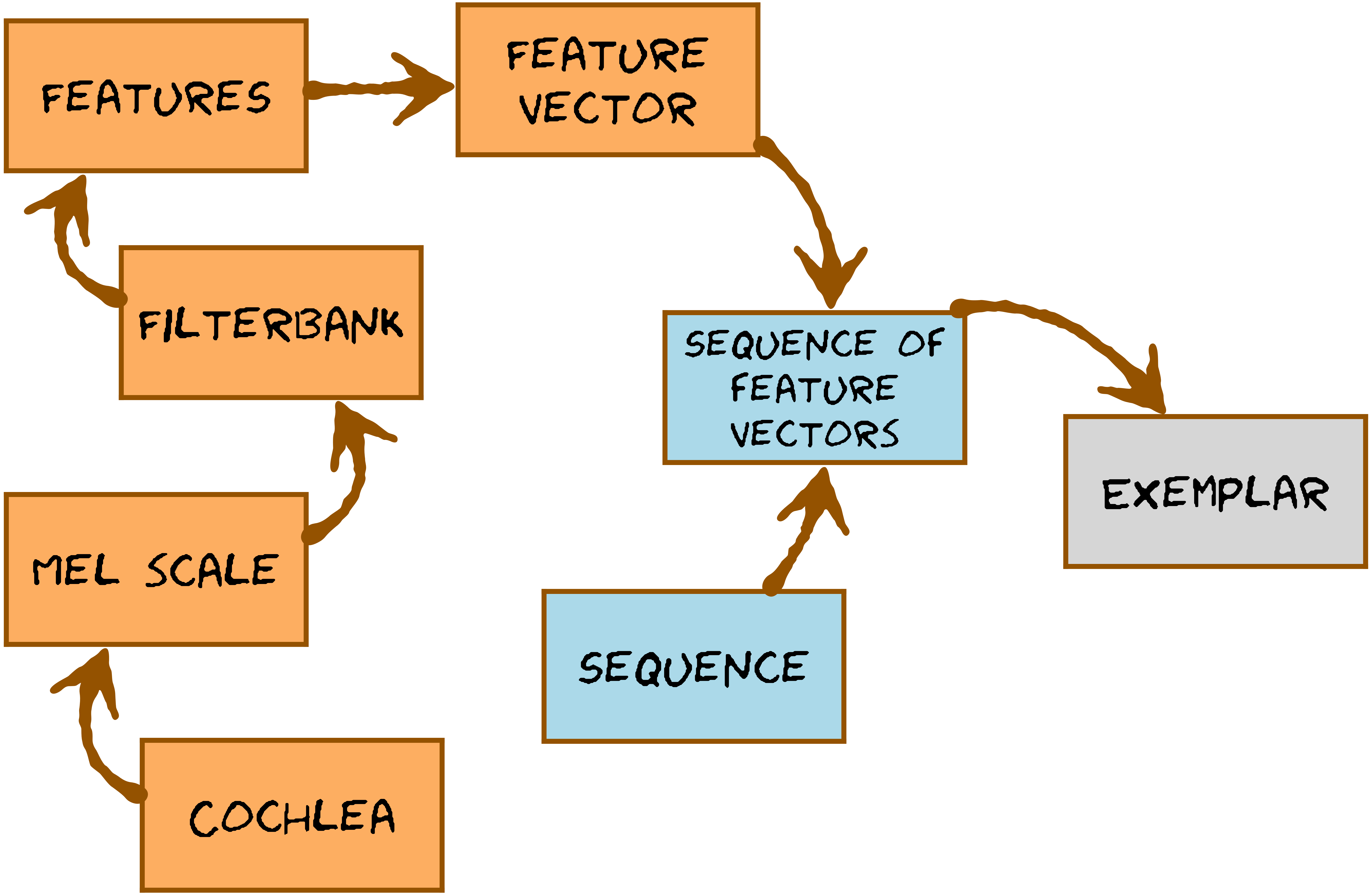
# Filterbank features for automatic speech recognition





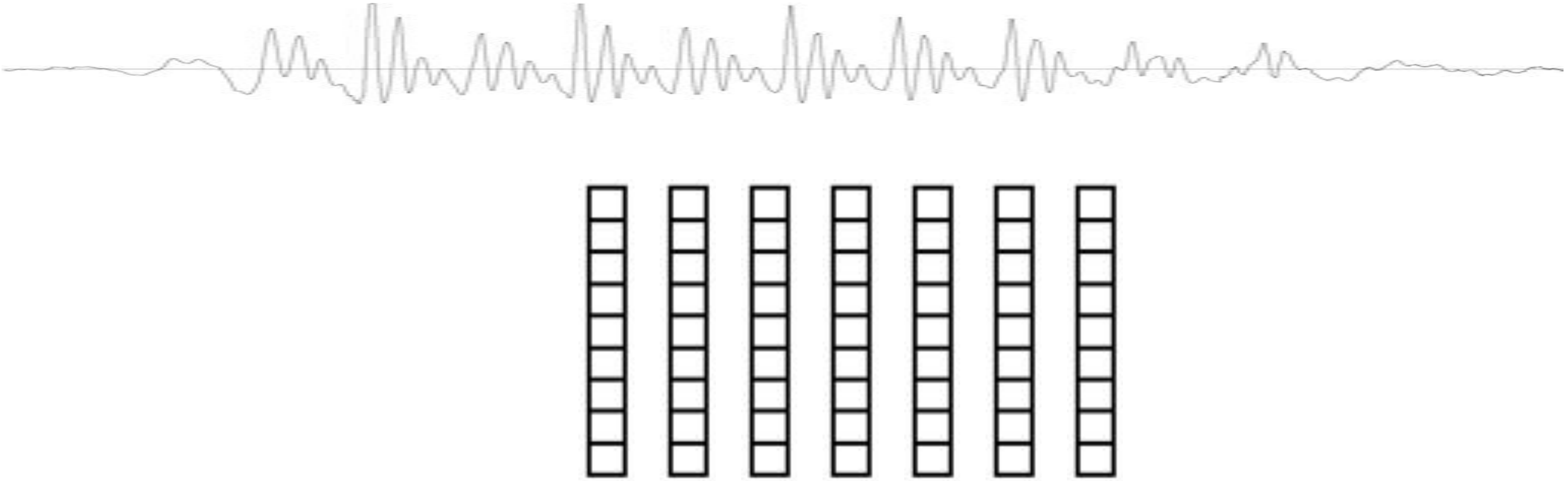
SEQUENCE OF FEATURE VECTORS

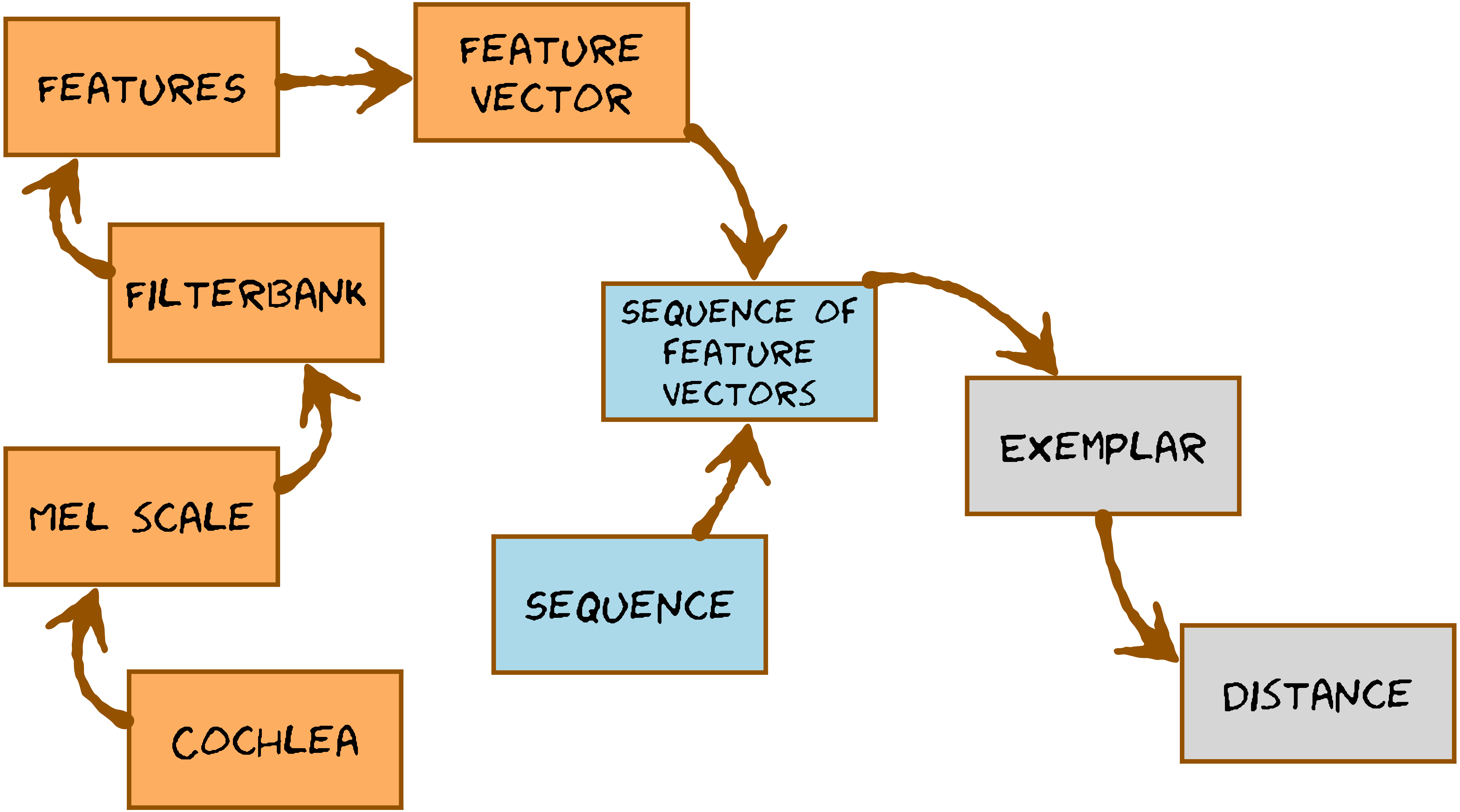
# Filterbank features for automatic speech recognition


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

# “three”

EXEMPLAR

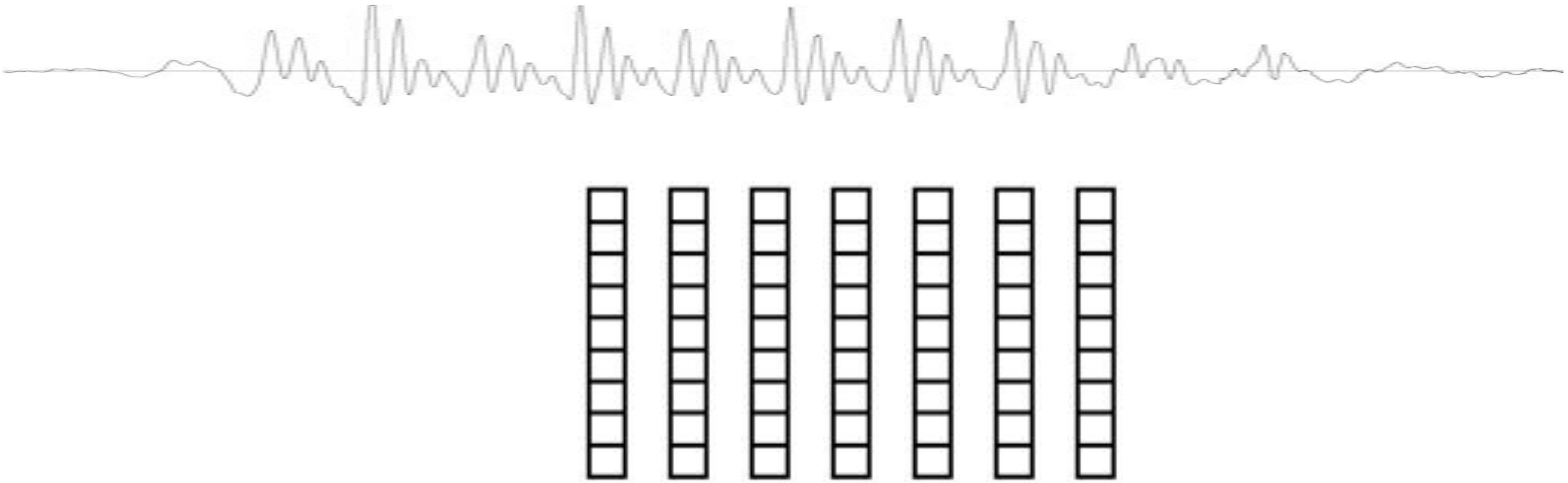




FEATURES
FEATURE VECTOR
FILTERBANK
SEQUENCE OF FEATURE VECTORS
MEL SCALE
EXEMPLAR
SEQUENCE
COCHLEA
DISTANCE

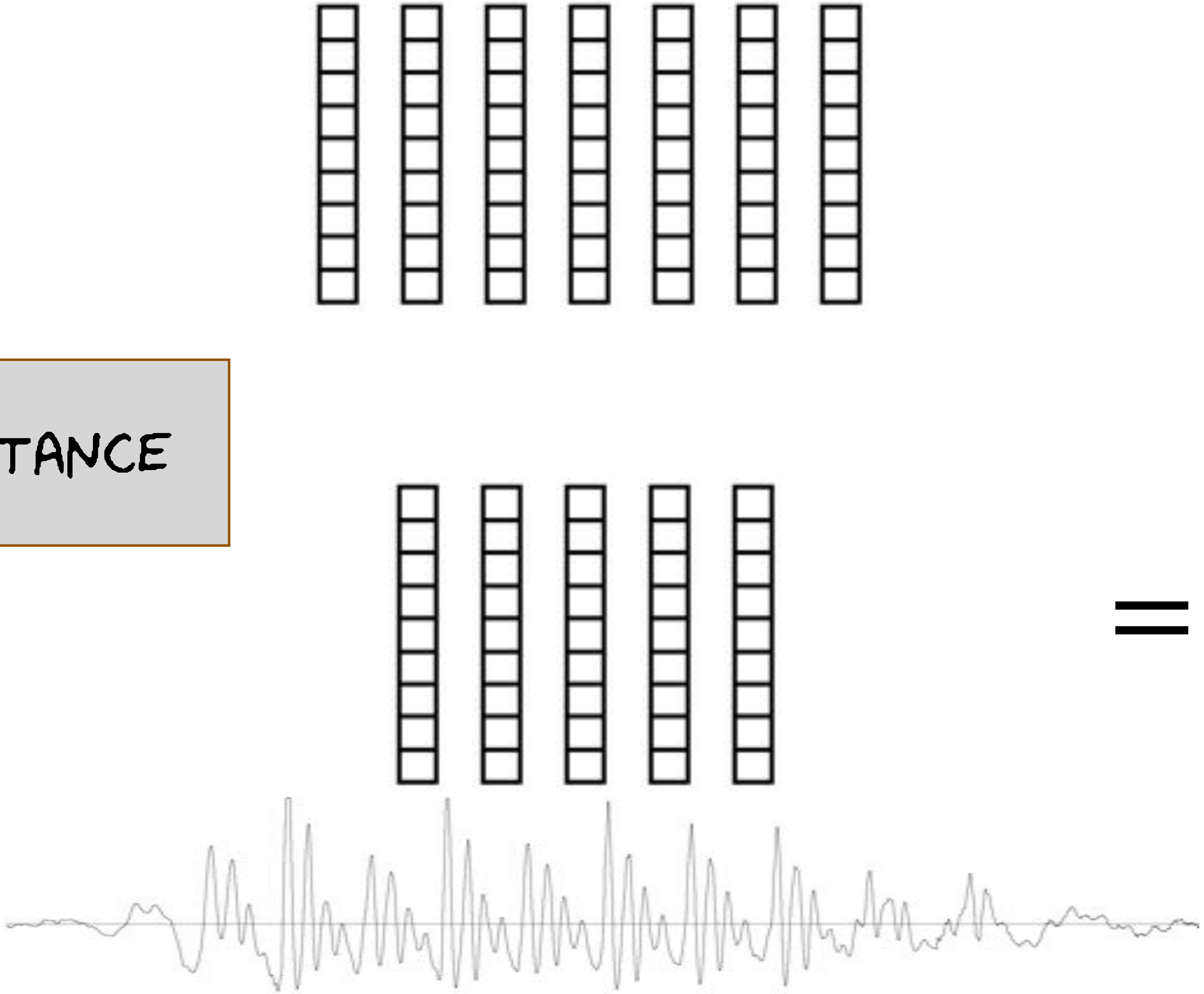
# “three”

EXEMPLAR



EXEMPLAR

“three”



DISTANCE

“???”

global distance

$$= \sum \text{local distances}$$

EXEMPLAR

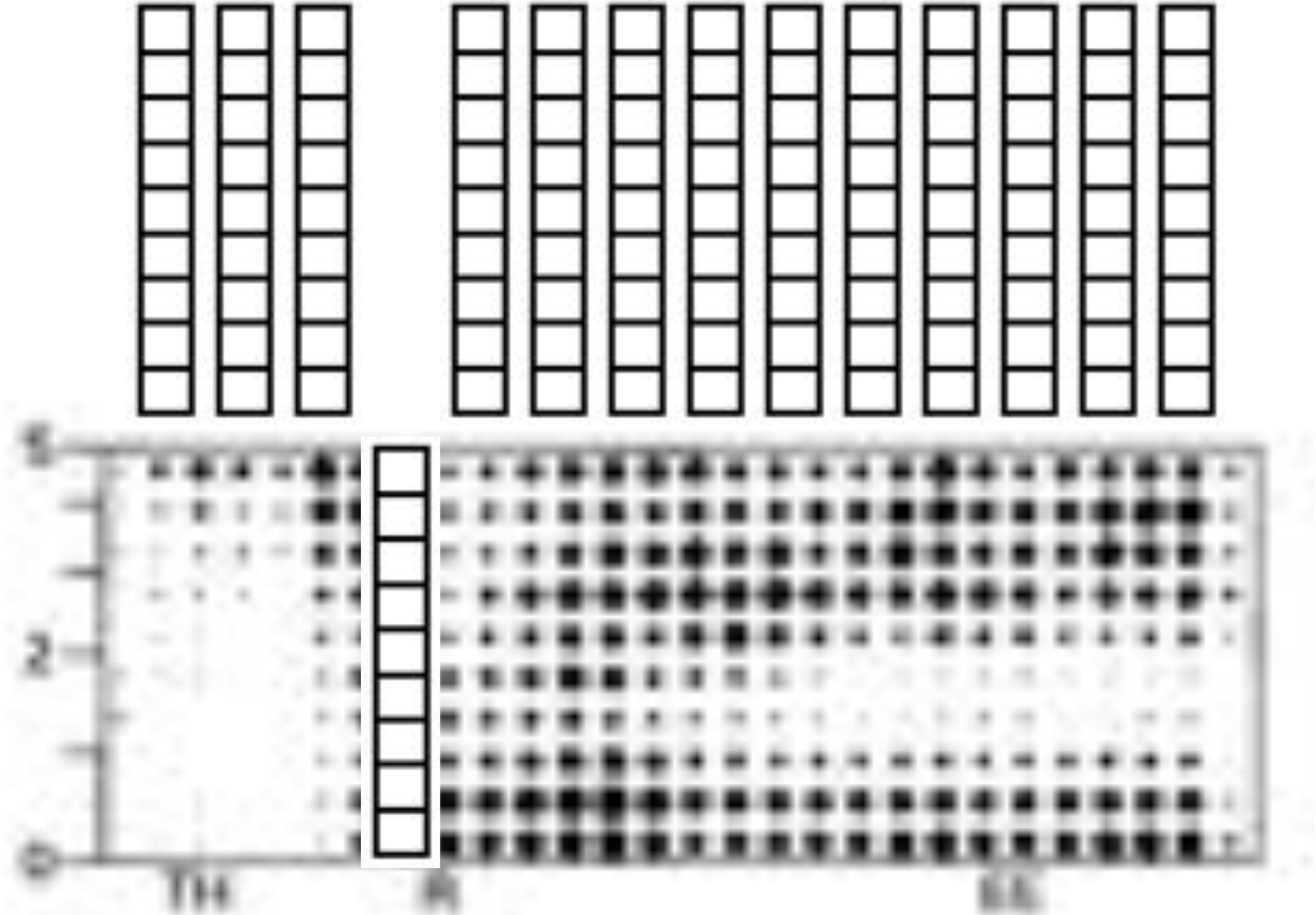
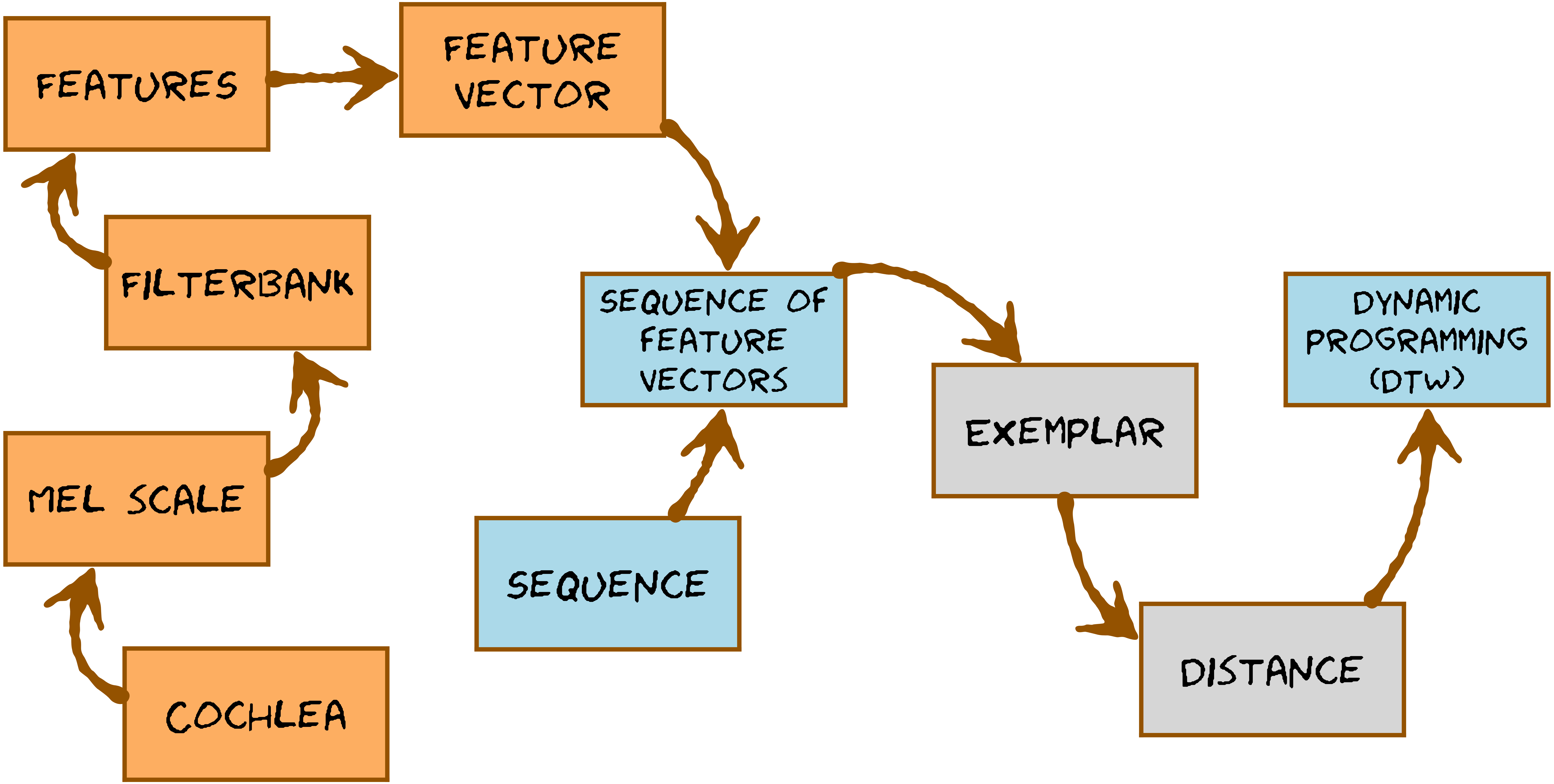


Image credit: Figure 8.1 from Holmes & Holmes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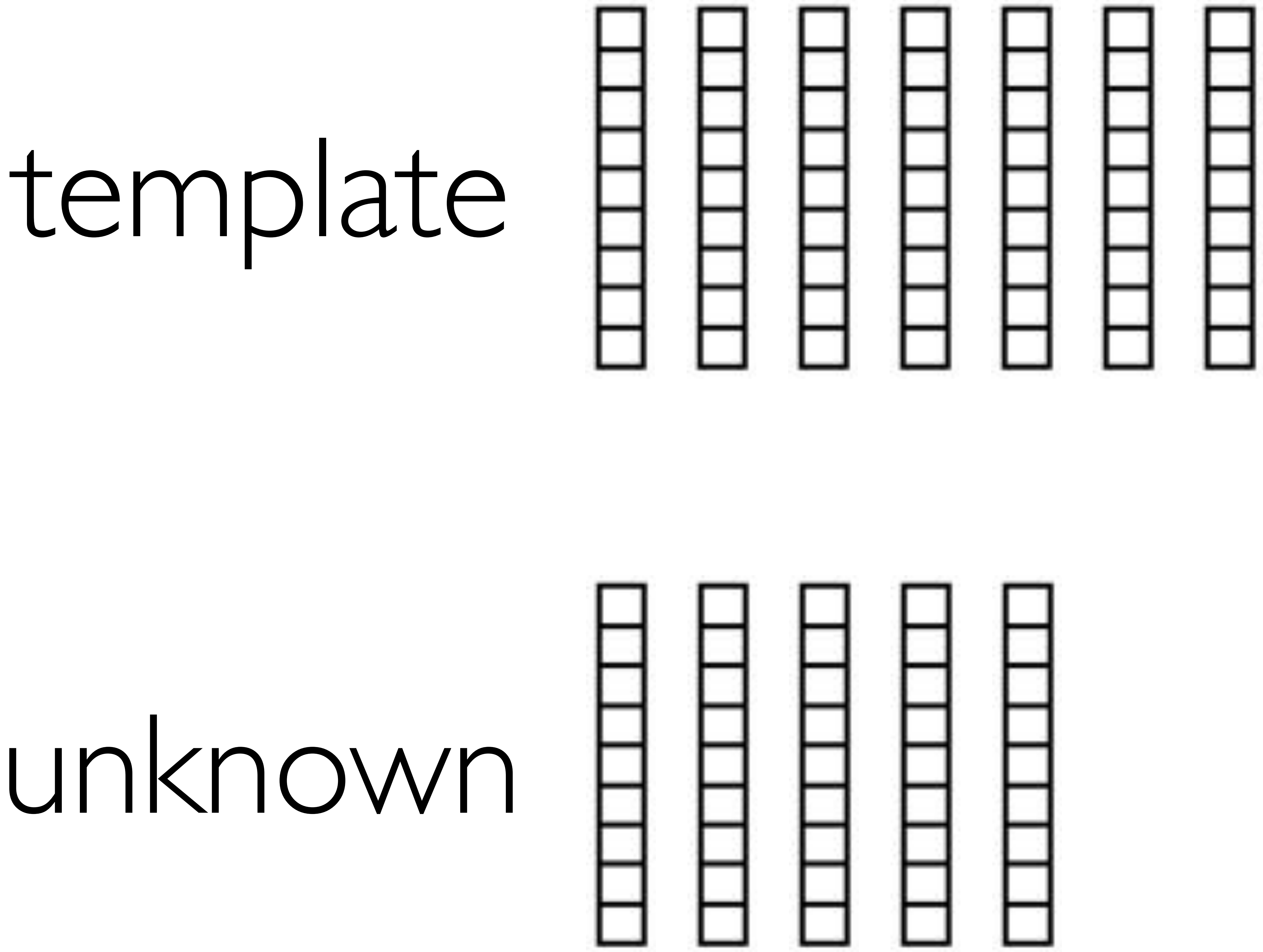
# Pattern matching by Dynamic Time Warping



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

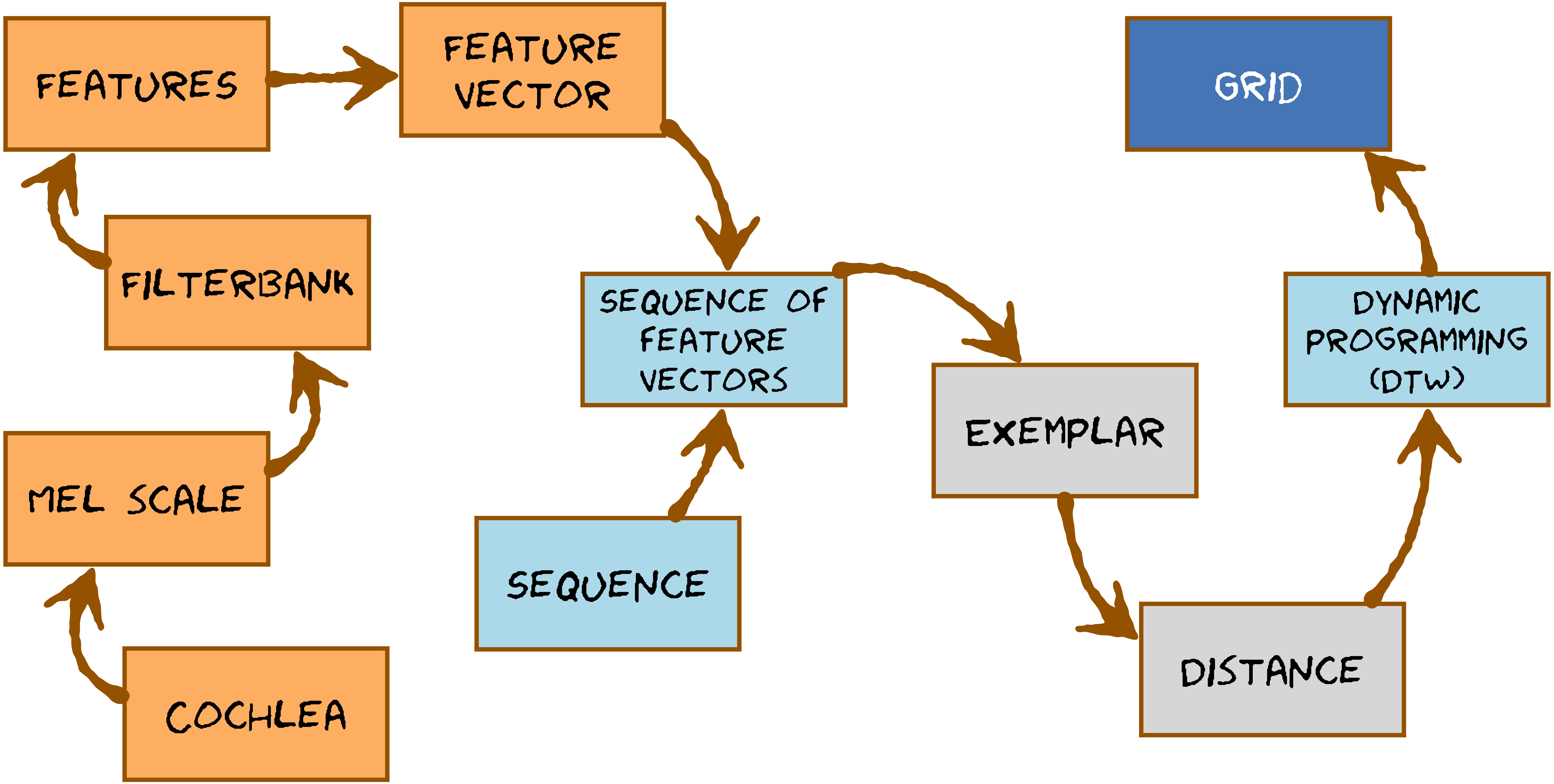
**Getting harder**

- 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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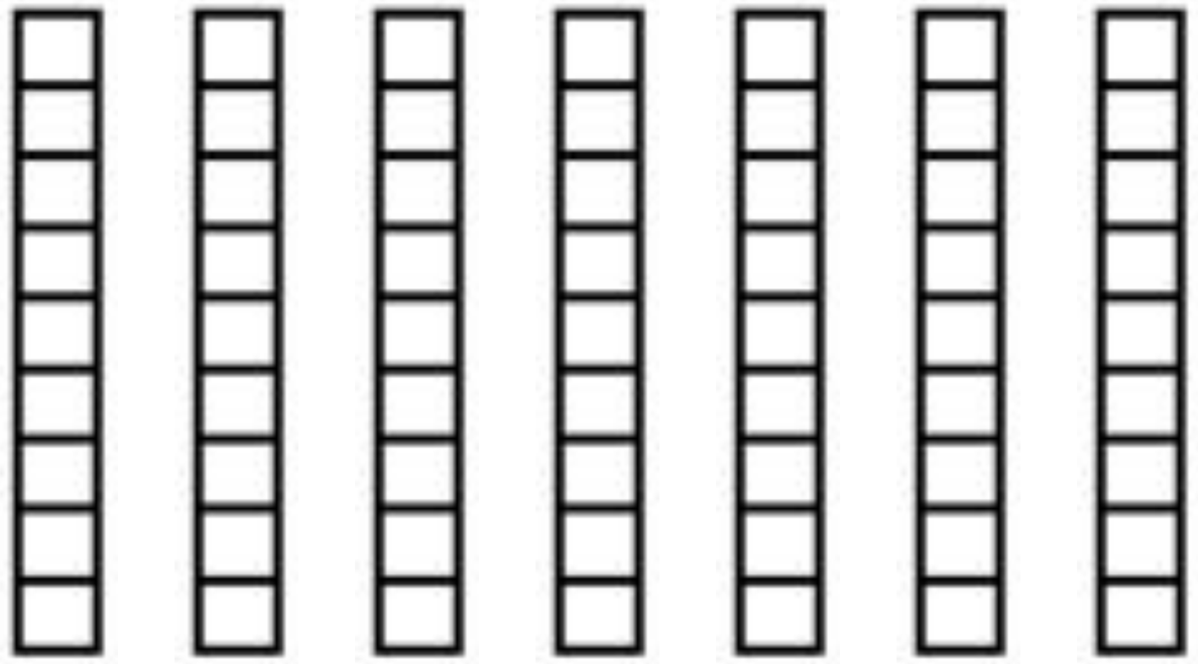
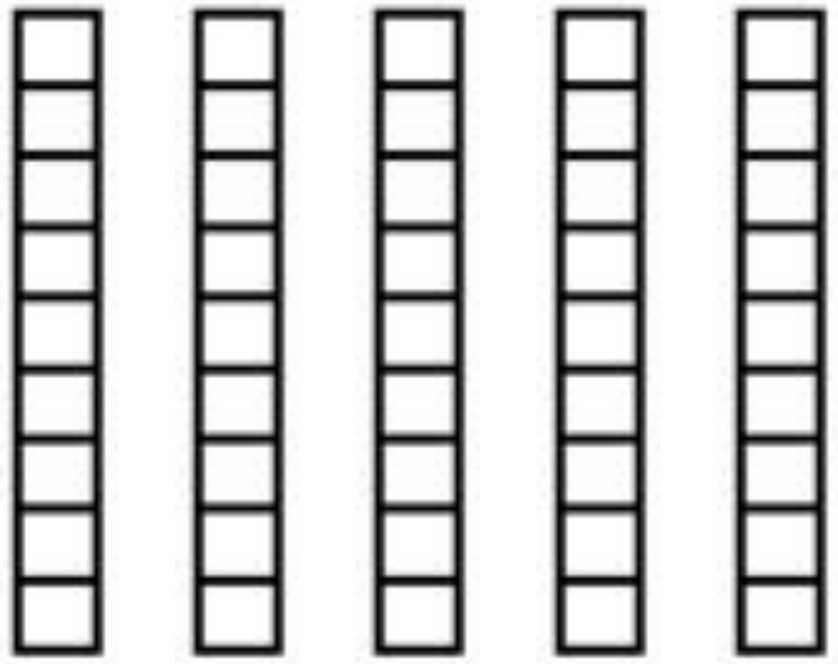
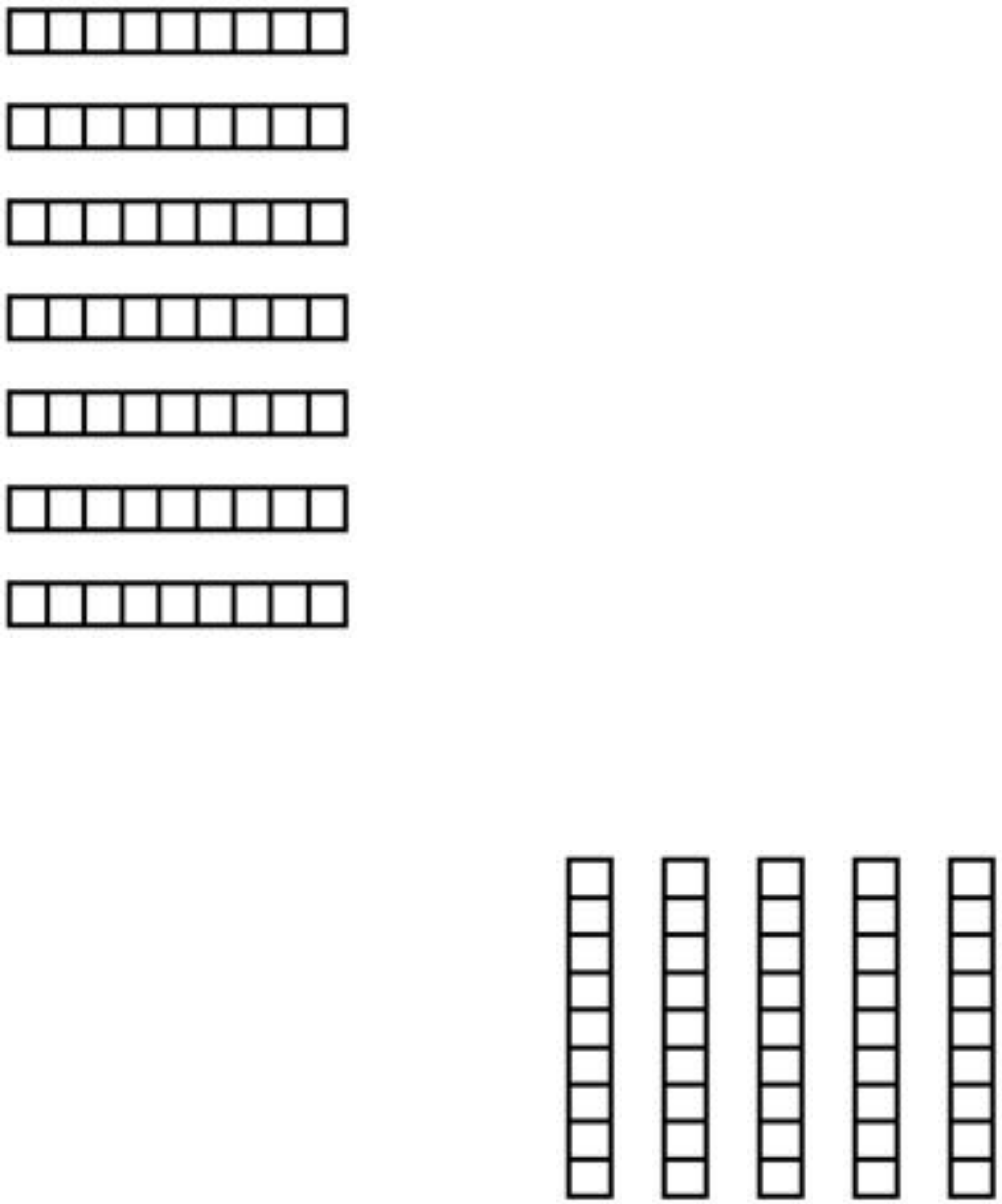
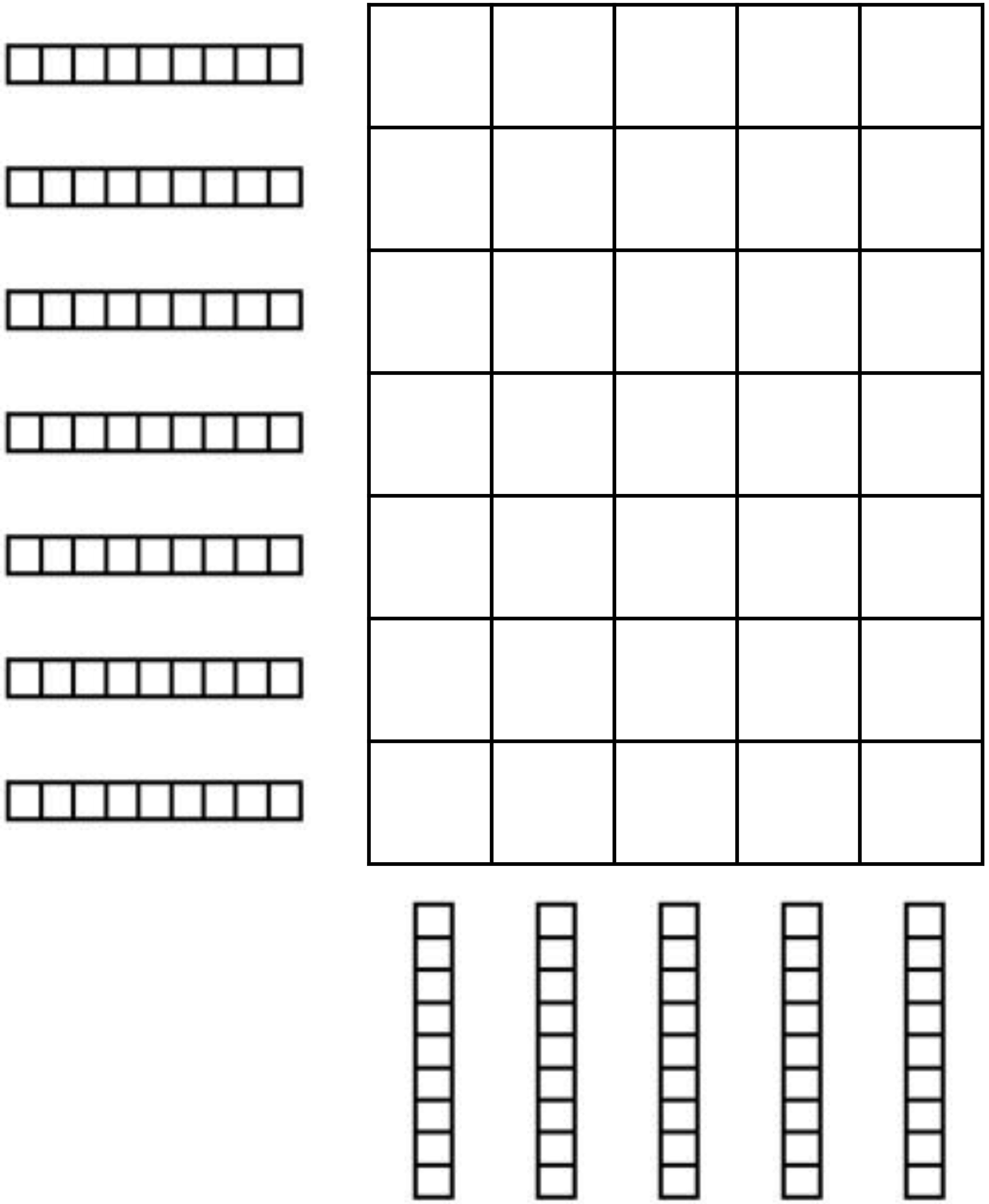
‘‘three’’





‘‘???’’





GRID

SEQUENCE OF FEATURE VECTORS

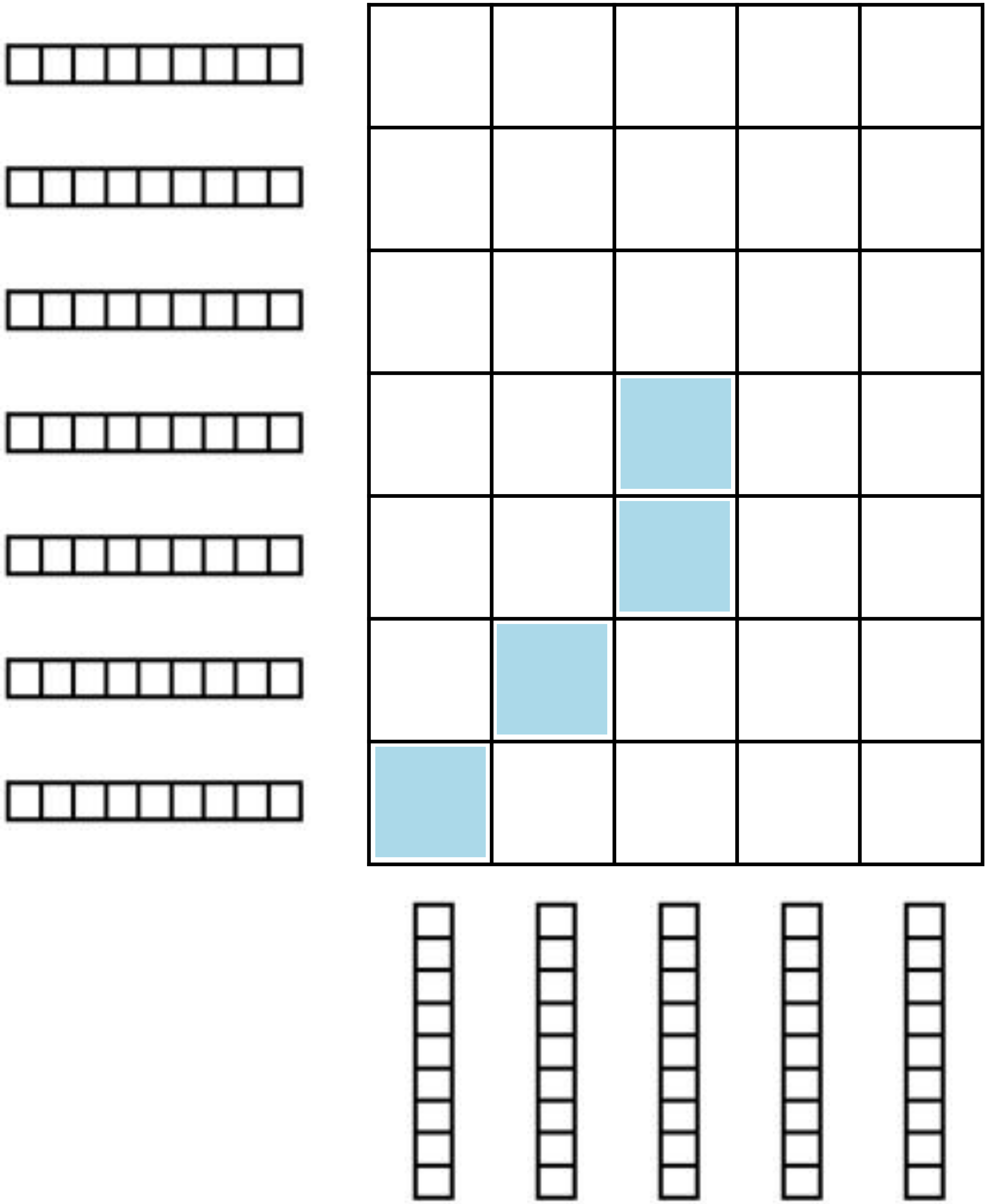
global

DISTANCE

local

SEQUENCE OF FEATURE VECTORS

DYNAMIC PROGRAMMING (DTW)



1 , 1

2 , 2

3 , 3

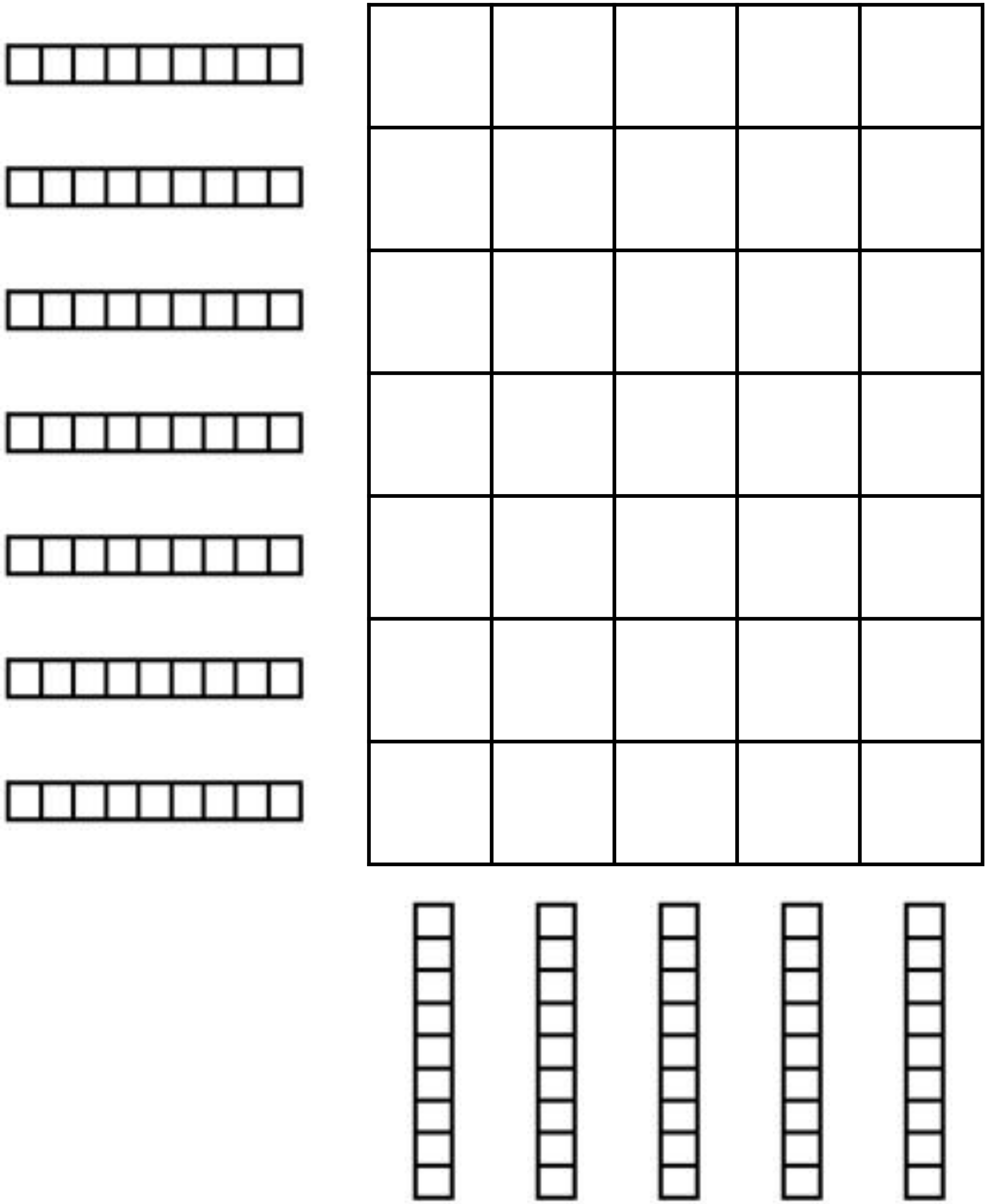
**4 , 3**

5 , ?

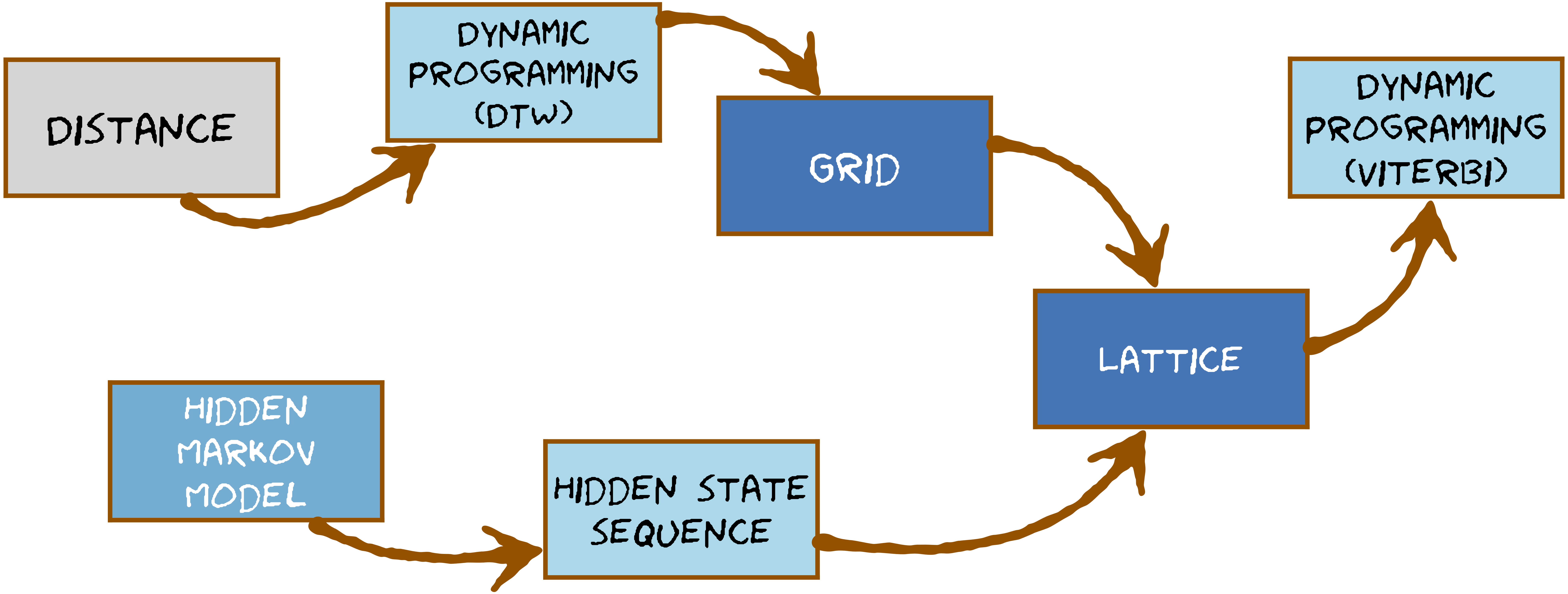
6 , ?

7 , ?

DYNAMIC PROGRAMMING (DTW)



# What you can learn next


DISTANCE

DYNAMIC PROGRAMMING (DTW)

GRID

LATTICE

DYNAMIC PROGRAMMING (VITERBI)

HIDDEN MARKOV MODEL

HIDDEN STATE SEQUENCE

# 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 9

- 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 8