

# Deep learning in practice a Text-to-Speech scenario

*6th Deep Learning Meetup*

Kornel Kis

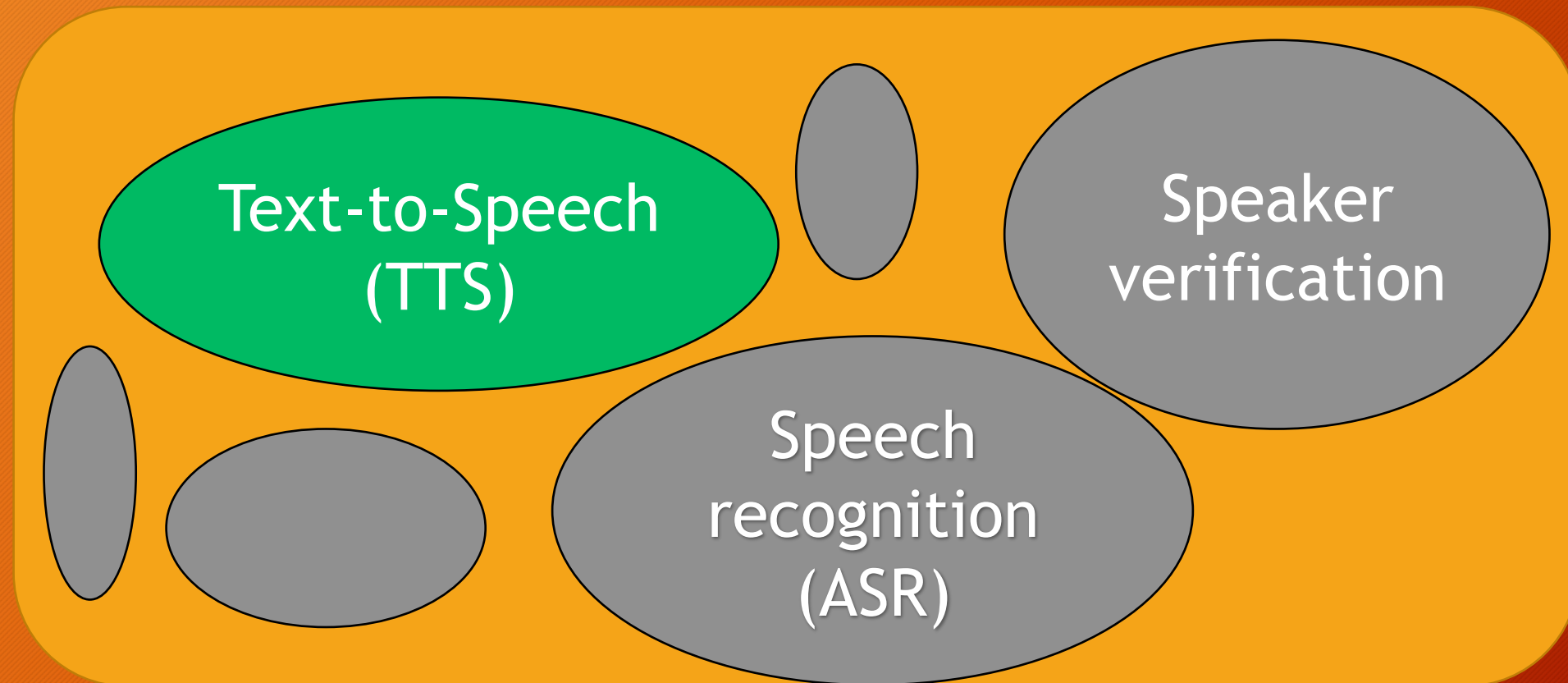
Vienna, 12.10.2016.

# Main Topics

- Speech technology (fundamentals)
- Deep learning in practice
- Ensemble learning (a bit)



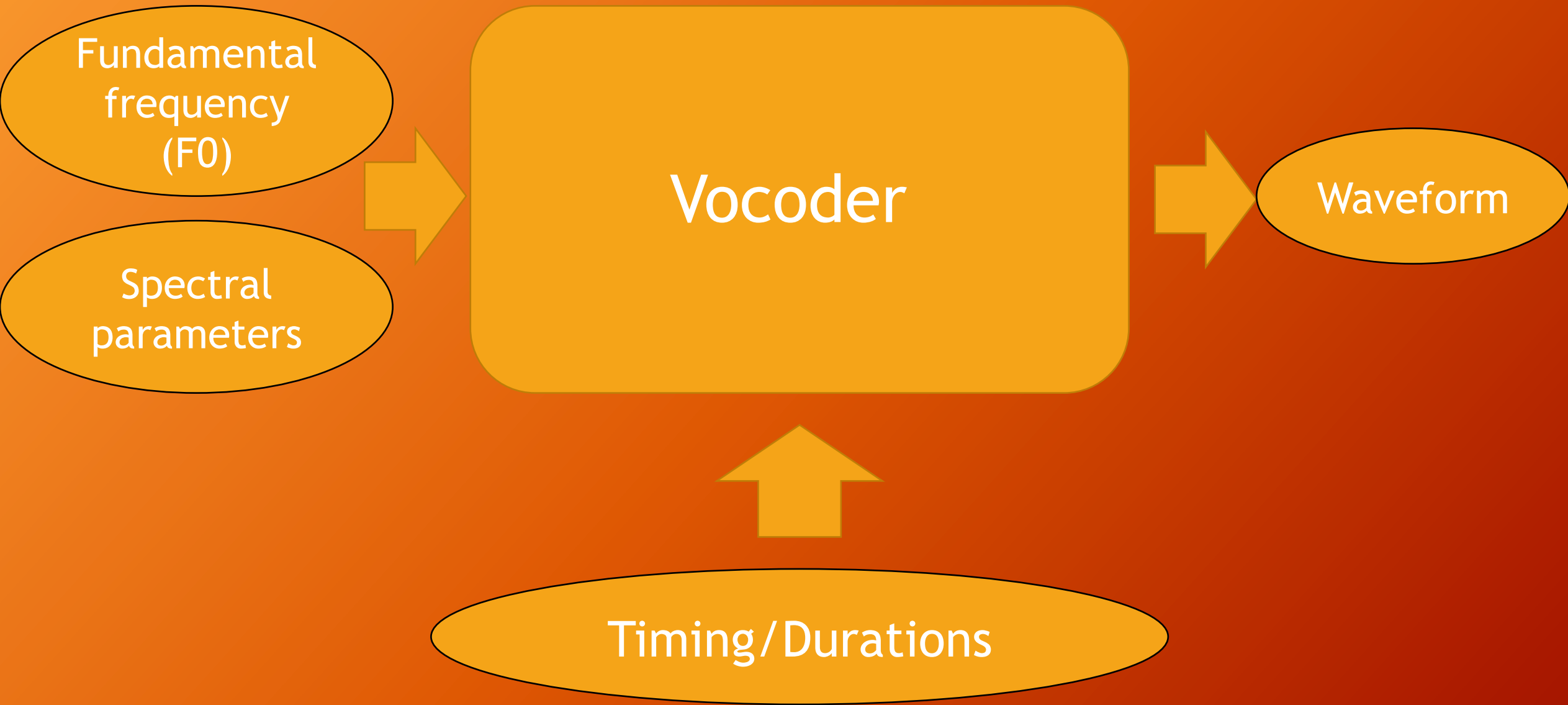
# Speech technology

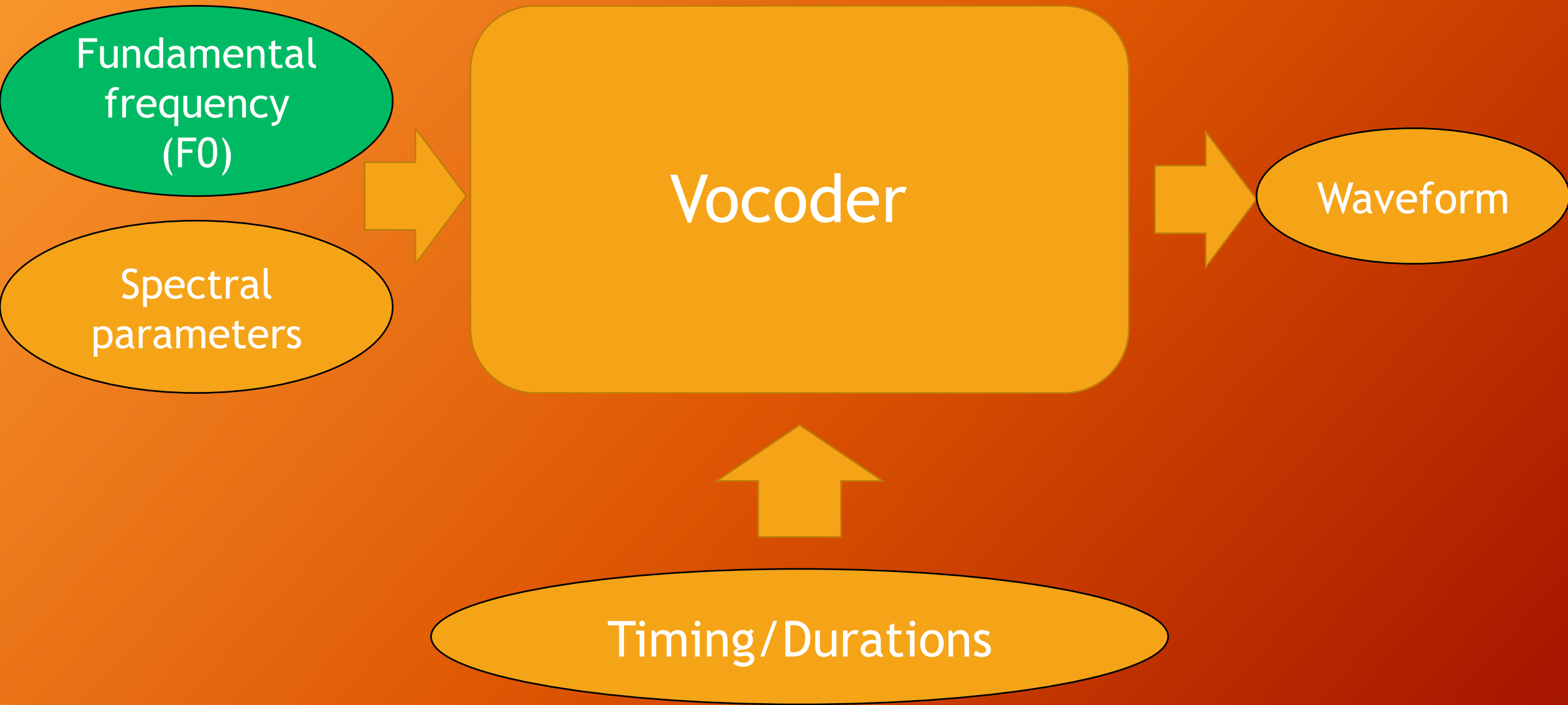


# Text-to-Speech - fundamentals

- Written text -> Waveform (.wav)
- A popular approach for general purpose synthesis:

*statistical parametric synthesis*

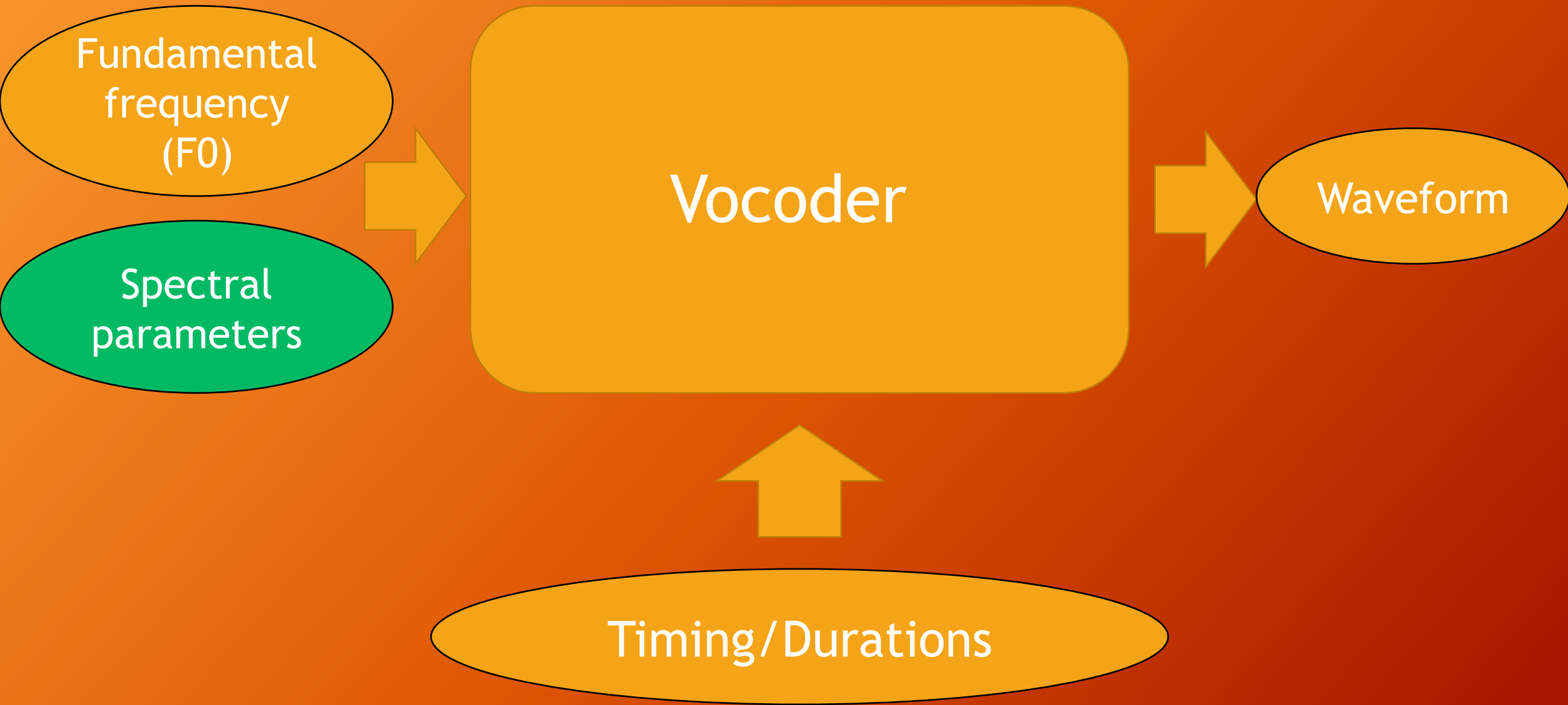






# The fundamental frequency

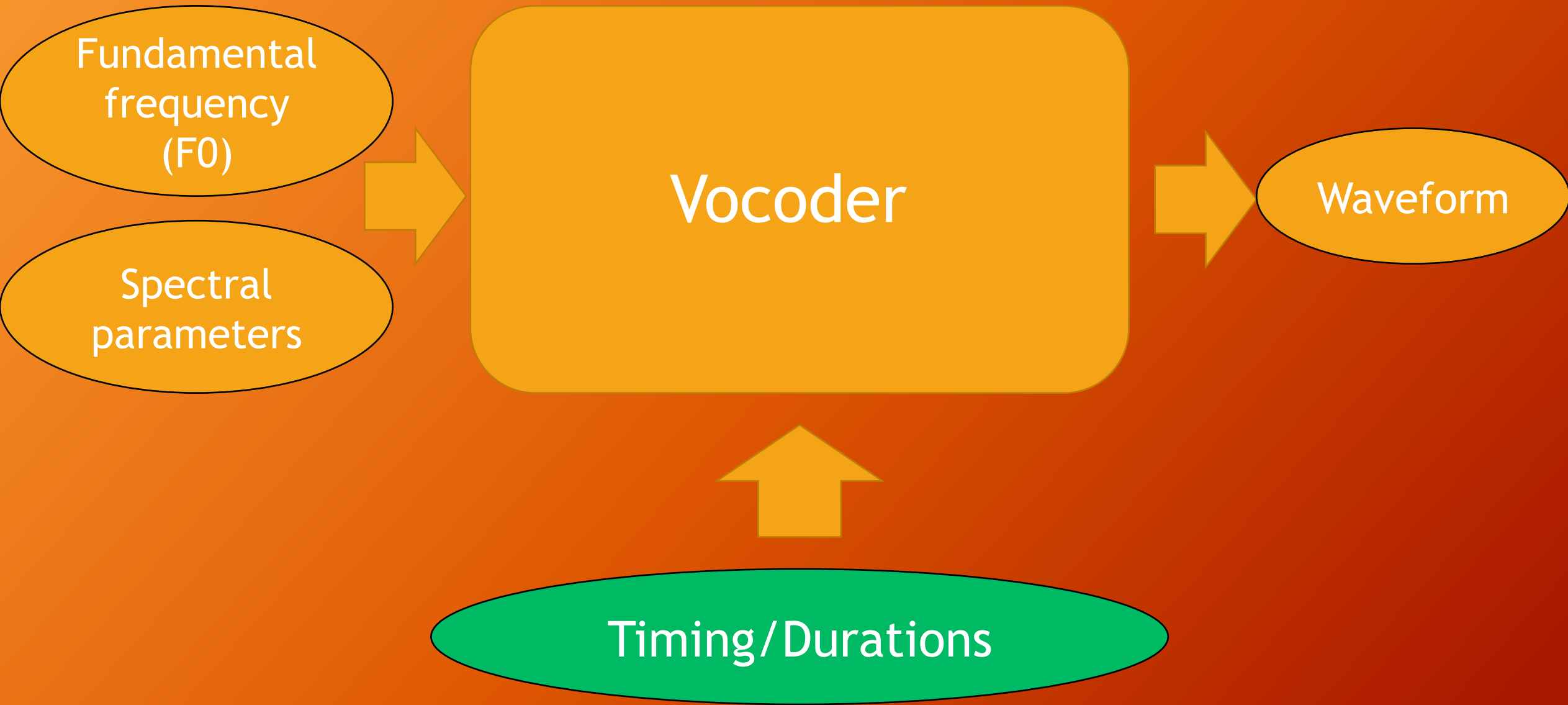
- Different for all speakers
- Real-valued 1D function of time
- Discontinuous (!) - voiced/unvoiced flag + interpolation





# Spectral parameters

- LPC (Linear Predictive Coding) coefficients
  - Used to capture the information of speech on higher frequencies
- Depth can vary: 12-48 (usual: 24+1 members.)



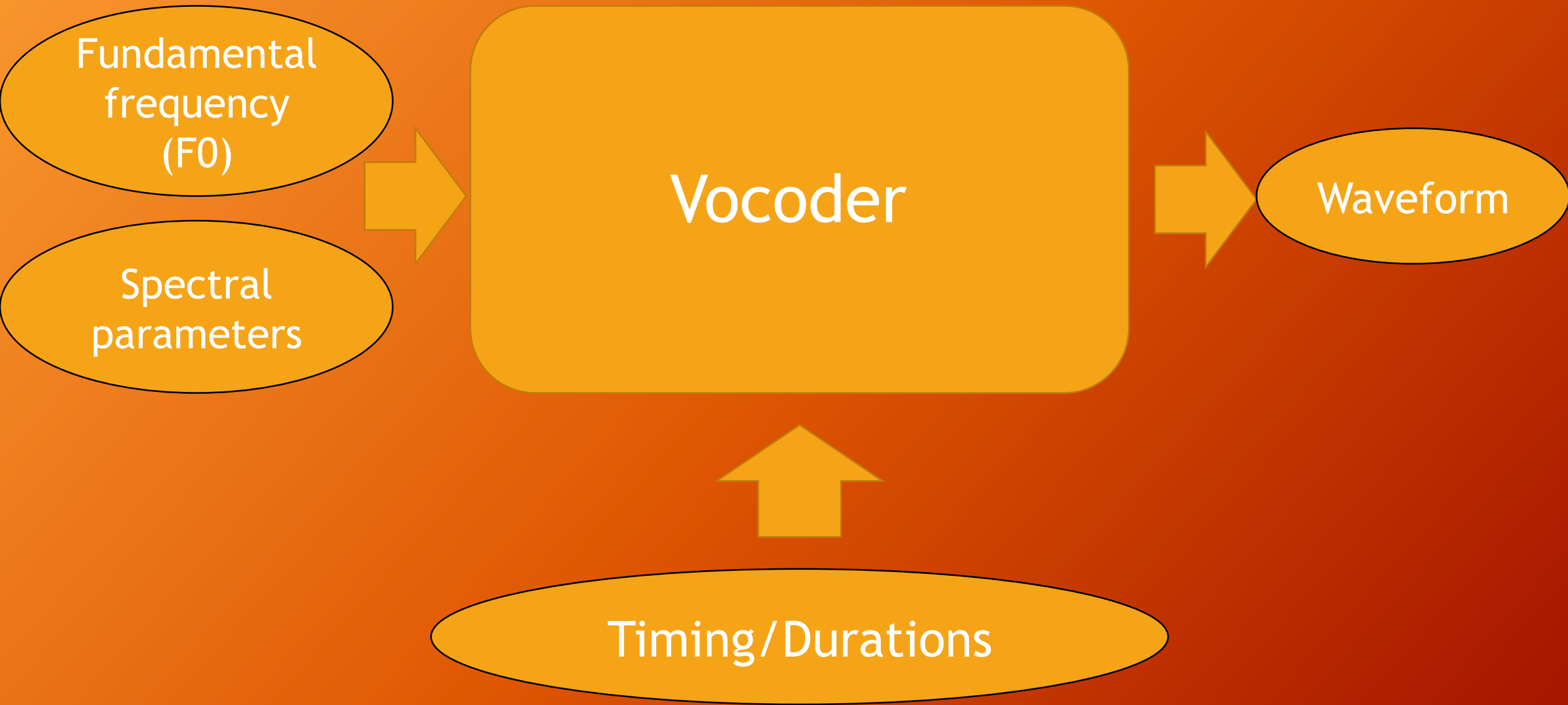
# Timing/Duration

- When is the first/next phoneme starting?
- How 'long' is a phoneme?



- Has to be modeled on a different, smaller neural net





## Database

~2 hours of recorded audio from a speaker (.wav files)  
Short, declarative sentences

Phonetic  
transcripts

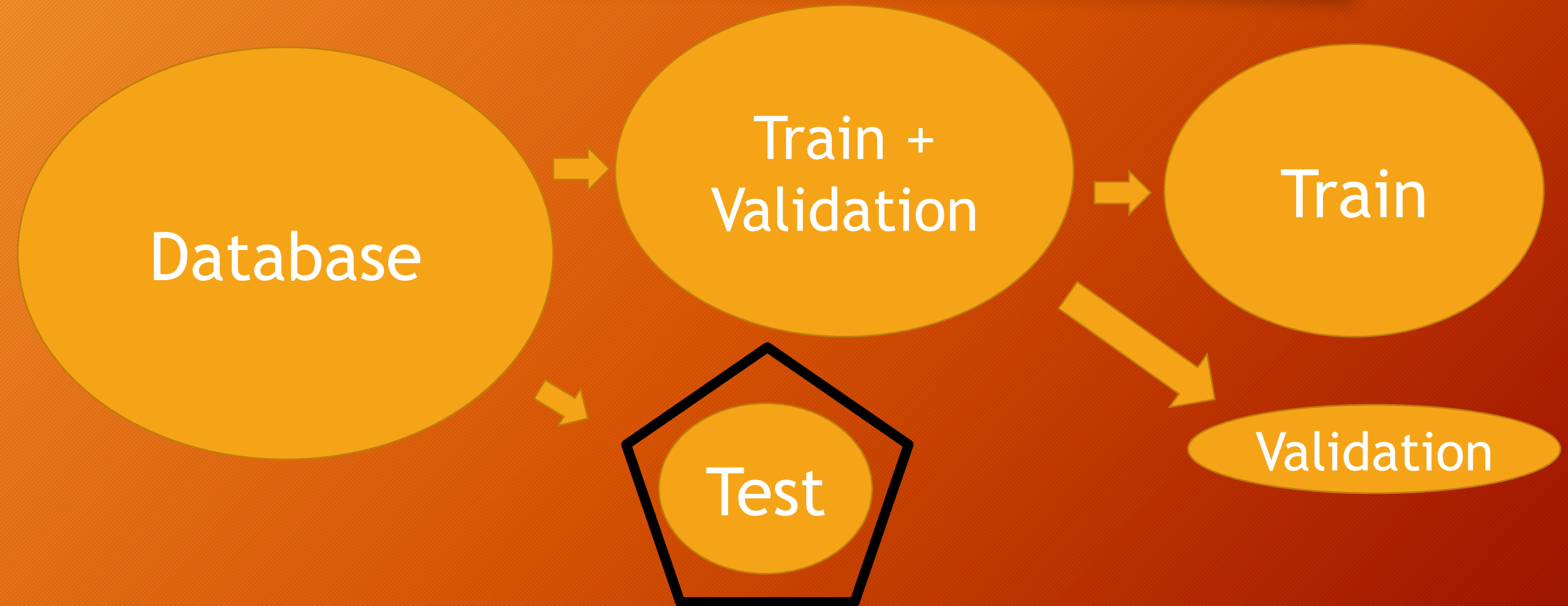
Neural network  
input  
Statistical  
features

F0 extractor  
LPC coder

F0 + LPC  
ground truth



# Database splitting





## Input

Numerical  
features (25)

Binary  
features  
(5\*68)



## Neural Network



## Output

F0  
data(1)  
V/UV  
Flag(1)

LSP  
coeffs  
(25)

## Input

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## Neural Network



## Output

F0  
data(1)  
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LSP  
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(25)

# The input

- Binary features:
  - 'Quinphone' model (first and second neighbours in phonemes)
  - $5 * 68$  (Hungarian) = 340
- Numerical features - representing a broader context:
  - Examples:
    - Total number of phonemes in the current word/sentence
    - Duration of current phoneme (ms)
    - Prosodic stress level (sentence, word, phoneme etc.)



## Input

Numerical  
features (25)

Binary  
features  
(5\*68)



## Neural Network



## Output

F0  
data(1)  
V/UV  
Flag(1)

LSP  
coeffs  
(25)

# The neural networks

- Multi-Layer-Perceptron (MLP)
  - Stack of FC layers
  - Feedforward
- Alternative: LSTM, GRU etc. -> recurrent nets
  - Or CNN (very recent result -> WaveNet)

Why MLPs?



Deep MLPs  
(feedforward)

New idea:  
Backprop.  
through  
time

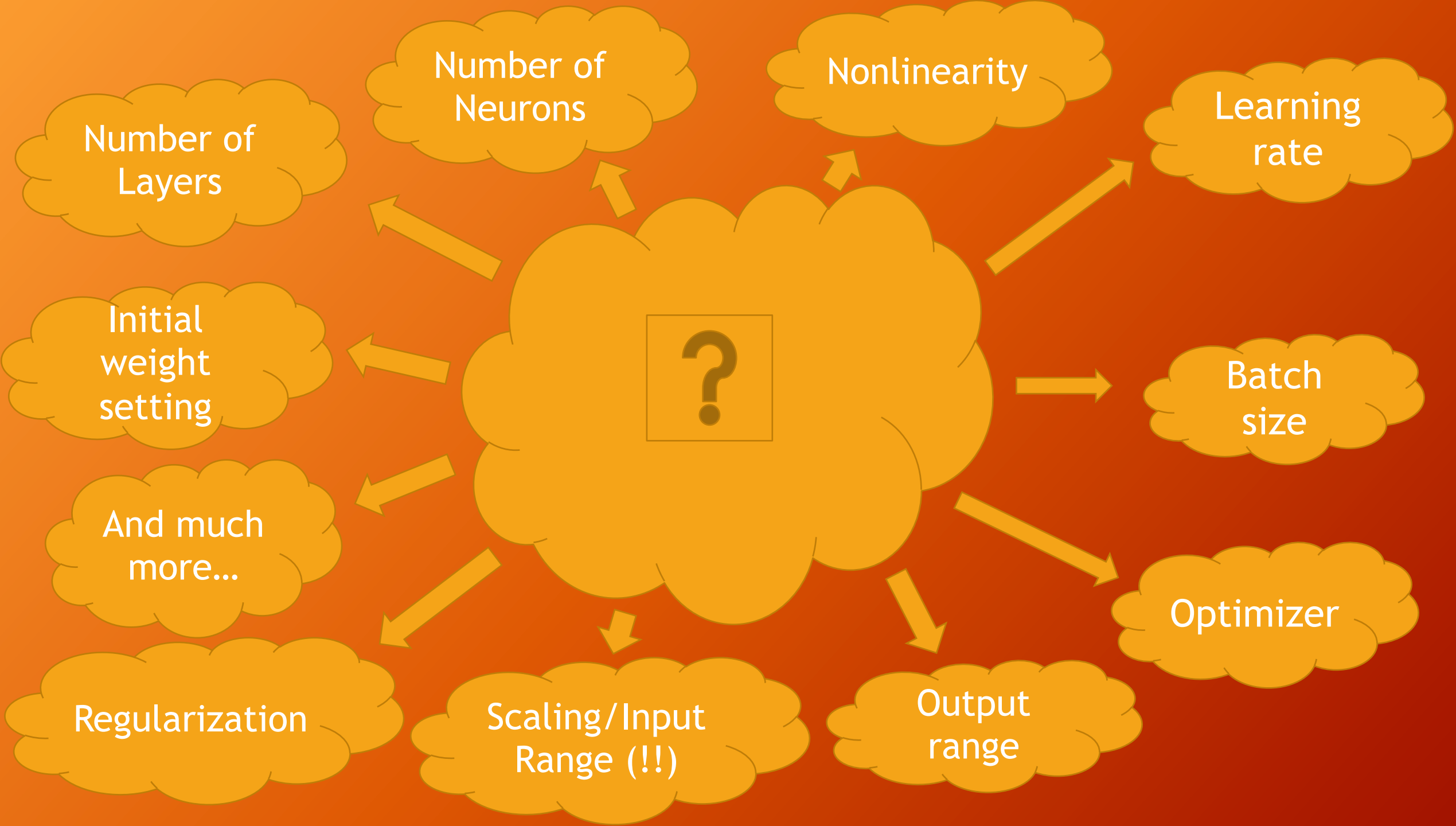
LSTM, GRU  
etc.  
(recurrent)

New idea:  
Input is  
highly  
redundant

ConvNETs  
(feedforward)







# Number of Layers

- More than one 😊 -> 'deep learning'
- Type: integer
- 'usual' value: 2-6 (MLP)
- >10 -> vanishing gradients problem



# Number of Neurons

- Fundamental unit of the network (weights + bias)
- Type: integer
- 'usual' value: 2- (few thousands)
- Training time - performance tradeoff
- Same number in each layer -> usually better
- Too many -> overfitting, too few - bad performance

# Non-Linear function

- Output =  $f(W*x + b)$ ,  $x$  is the input
- $f(...)$  is the nonlinearity
- Usually: 'ReLU' or something similar
- Sigmoid, tanh, -> not really...



# Learning rate

- Probably the most important hyperparameter
- $x += - \text{learning\_rate} * dx$
- manual setting -> minibatch gradient descent
- Type: float (0.0-1.0)
- 'usual' value:  $1e-5$  -  $0.3$  (no guarantees 😊)
- Larger nets -> usually smaller

# Batch size

- Can be tricky...
- HUGE training time - performance tradeoff
- Minibatch learning -> approximating the real gradient



# Optimizer

- 'Classic': Mini-batch with momentum
- 'Classic+': Mini-batch with Nesterov momentum
- Novel methods: RMSprop, Adagrad, Adadelata, Adam, Nadam ...

# Input range/output range

- problem-dependent
- Should be close to the range of network weights
- Proper scaling of input is essential
  - Do NOT fit scaling on the test database !



# Regularization

- Weapons against overfitting
- Early stopping: recommended
- Dropout:
  - Type: float
  - 'Usual' values: 0.1-0.5
  - Very useful
- L1 and L2 regularization
  - L1 ~ a bit like PCA
  - L2 = weight decay

# Initial Weight settings

- Some form of random initialization
- Examples: uniform, orthogonal, lecun\_uniform, glorot\_uniform etc.
- Better choice may speed up the learning process



- More about this here:  
<http://yann.lecun.com/exdb/publis/pdf/lecun-98b.pdf>
- Yann LeCun et al. : Efficient Backprop

# Some hints for training

- Training error / valid error should be close -> if training goes down, valid not -> overfitting
- Do not use the test database in any way during training !
- Always make separate evaluation of the results (not just the error rate)
- Use a fast GPU (or several fast GPUs...)

# Hyperparameter optimization

- Search in the space of hyperparameters
  - Usual dimensions: learning rate, batch size, neuron number, layer number
- Approaches: Manual Search, Grid Search, Random Search, etc.

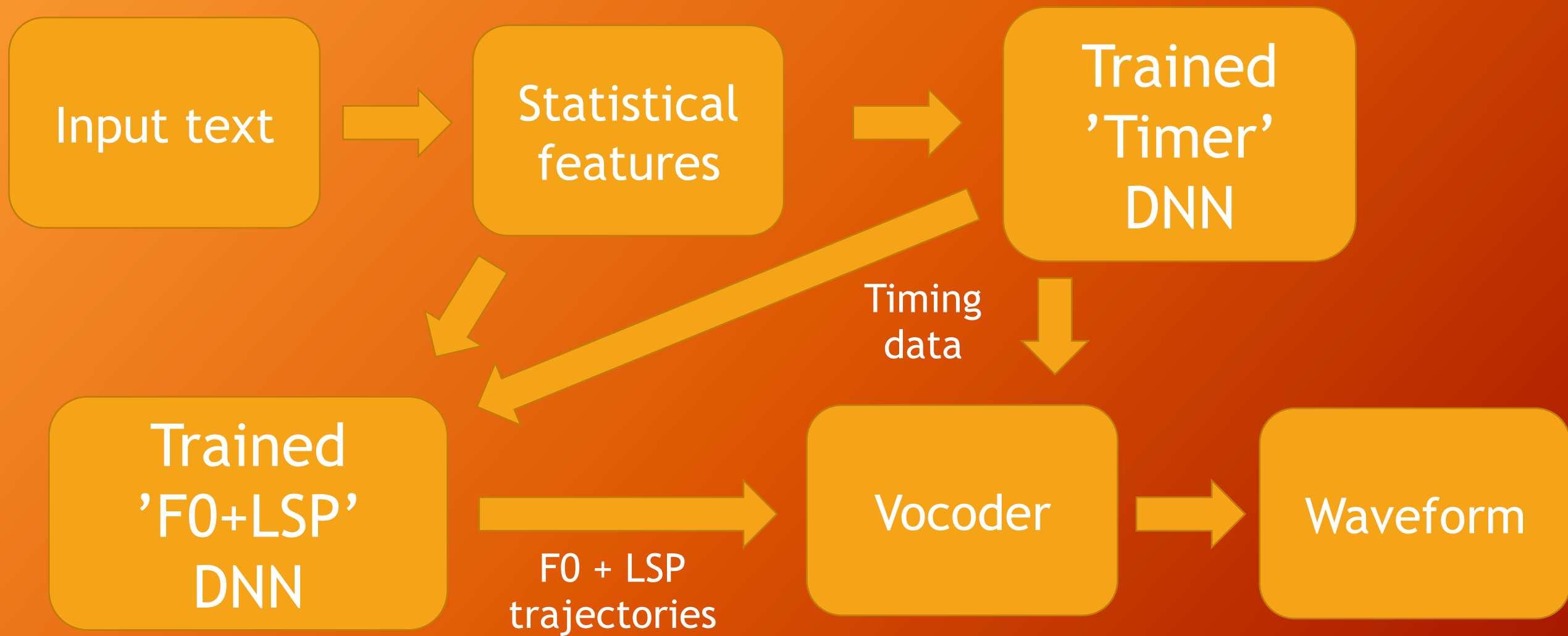


# Hyperparameter optimization

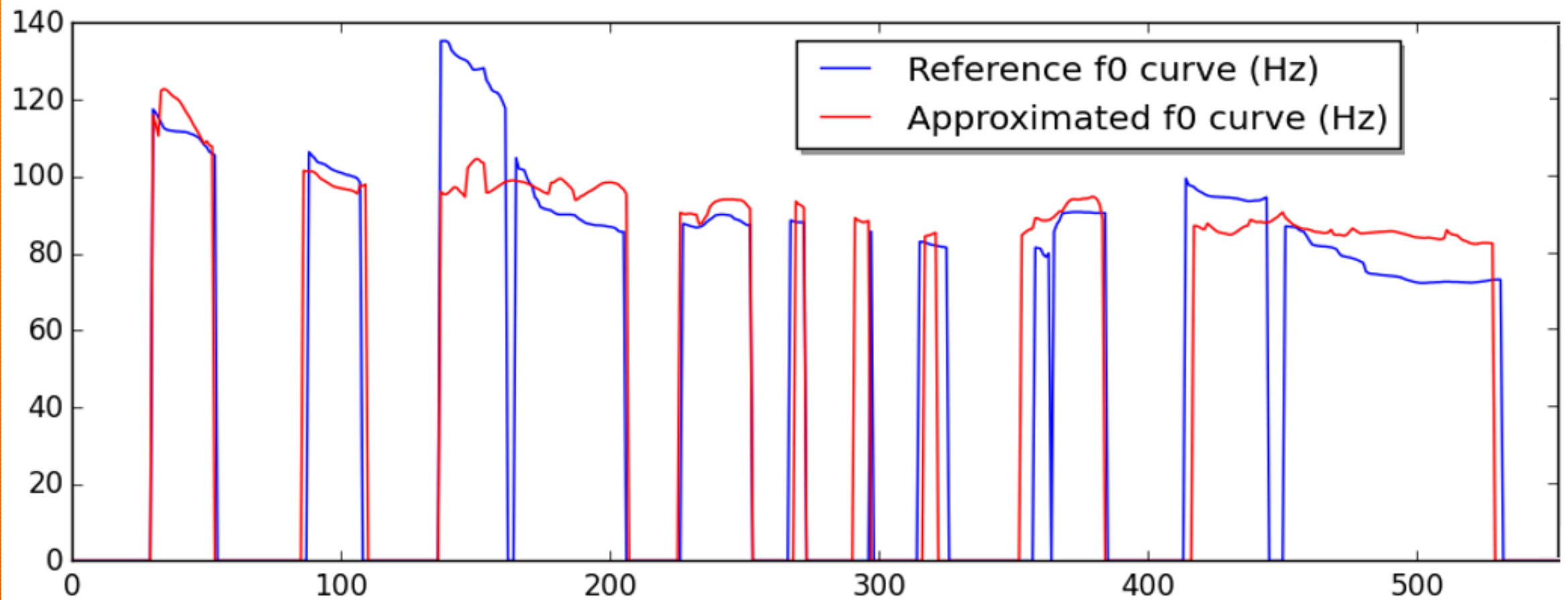
- Manual search: not very effective
- Grid search: good, but very time-consuming
- Random search: probably the best



# The complete DNN-TTS (testing)



# Results



# Ensemble learning

- Idea: Group of specialists OR group of weaker members working together
- Good way to get a little bit better results from our system
- The members does not have to be neural networks!

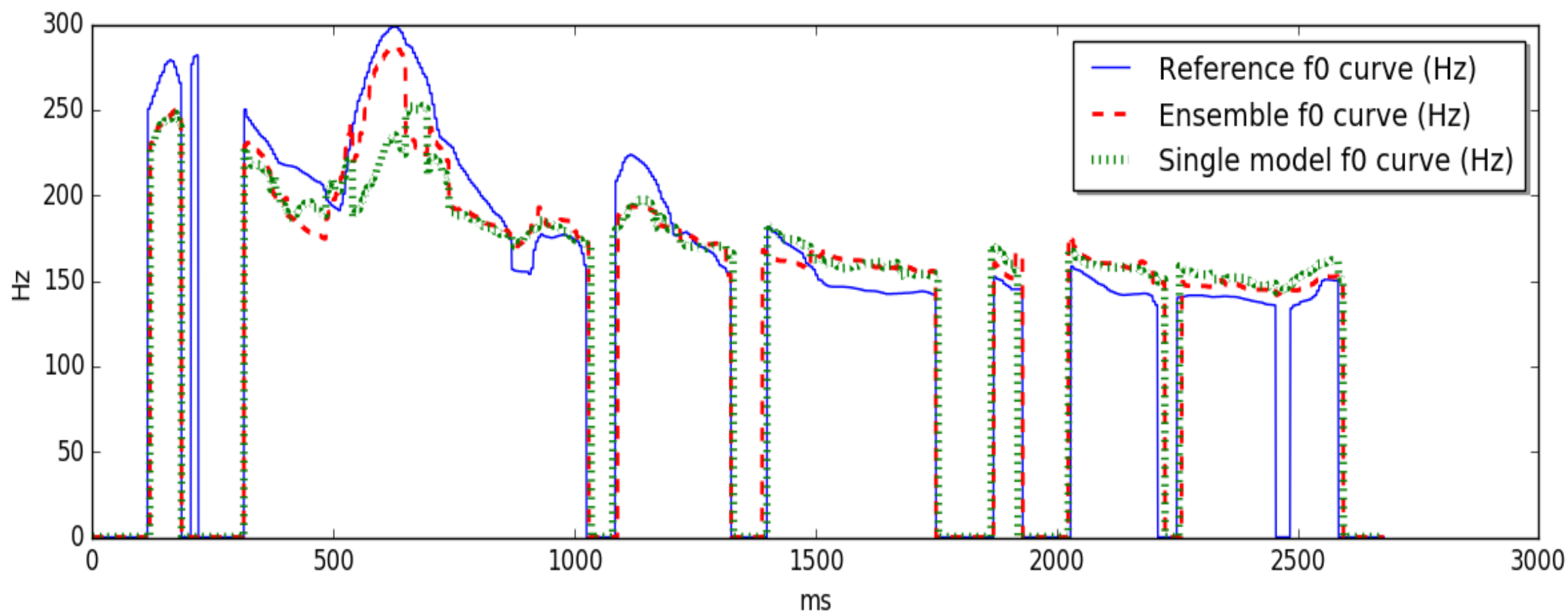


# Ensemble in speech technology (our idea)

- Train individual nets on different parts of database
  - The decision point the the level of prosodic stress
- Each member is responsible for one level only
- Goal: Better stress estimation



# Results



Thank you for your attention!

Questions are welcome