Sound object labeling

EECS 352 Machine perception of Music and Audio

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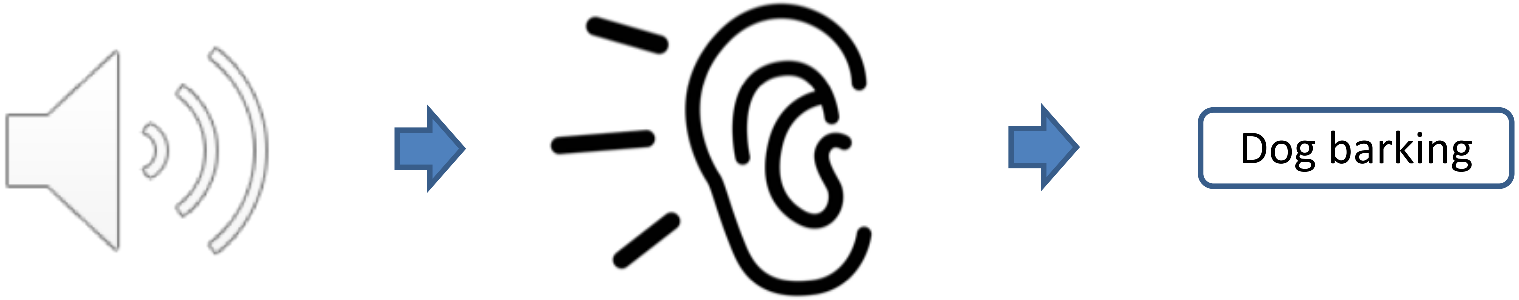
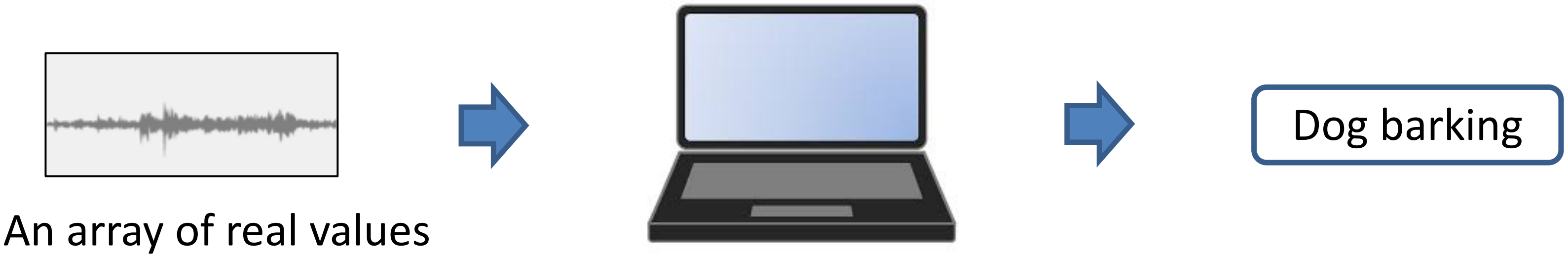
Sound object labeling



Dog barking

Goal

- Building a system that automatically labels an audio event

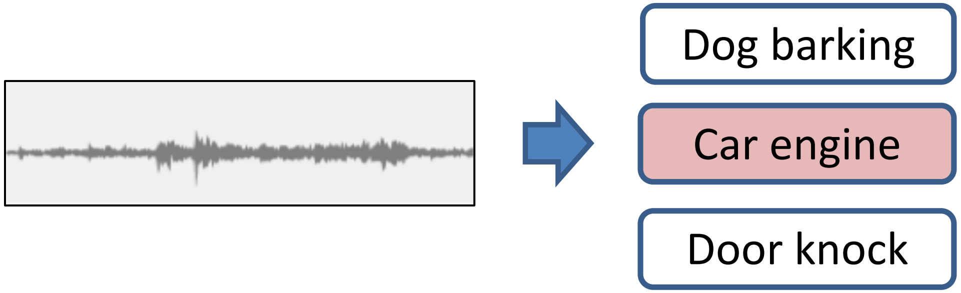


An array of real values

Dog barking

Tasks

- Audio classification

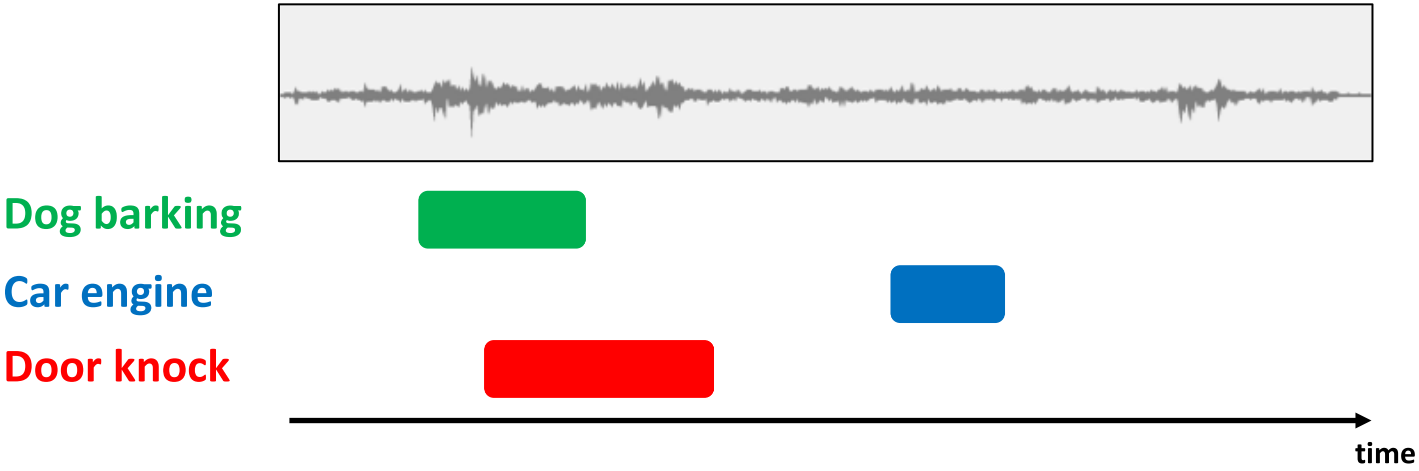


Dog barking

Car engine

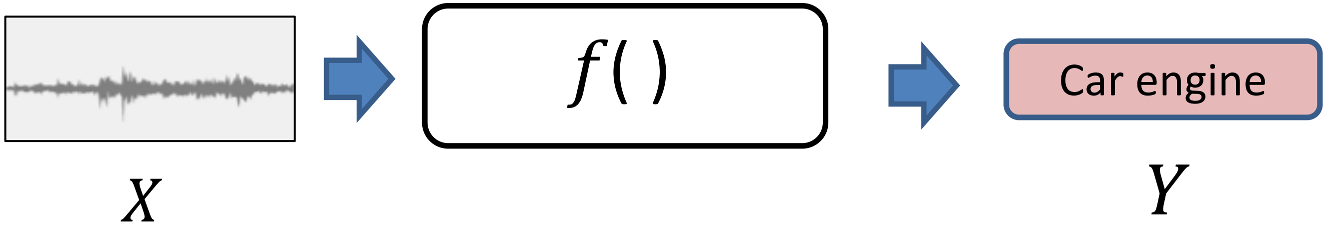
Door knock

- Sound Event Detection (SED)



MACHINE LEARNING: CLASSIFICATION

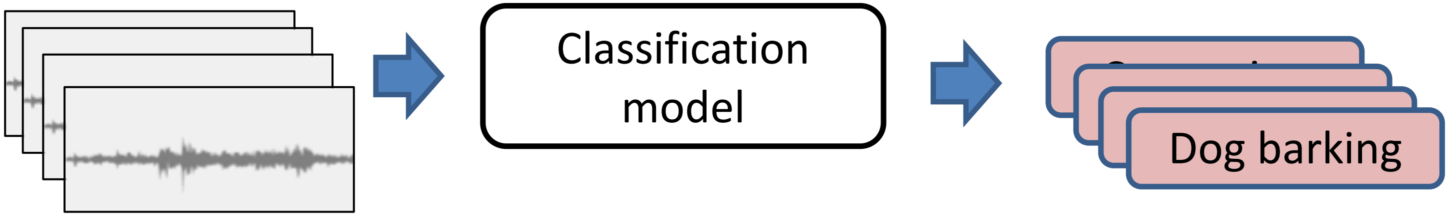
Supervised learning from data



Function we want to learn → $Y = f(X)$
(Target function)

Training input

Ground truth labels



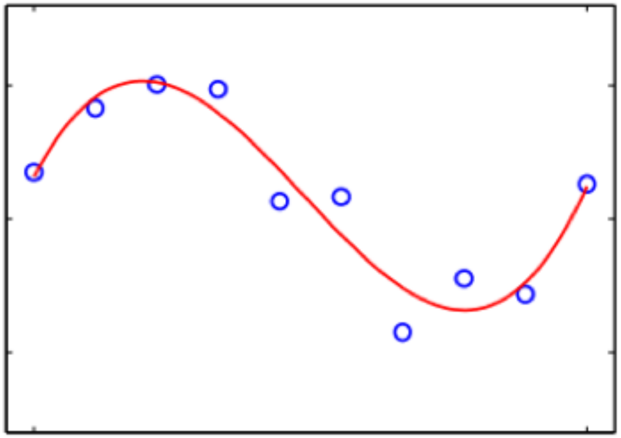
$X = \{x_{1,} x_{2,} \ldots, x_n\}$ $h(\ )$ $y = \{y_{1,} y_{2,} \ldots y_n\}$

Find a hypothesis function h such that $h(X) \approx f(X)$

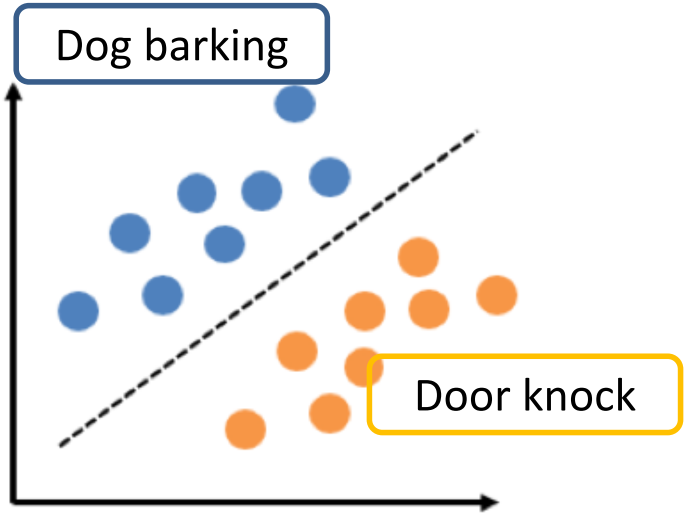
On the training data D = $\{< x_{1,} y_1 >, \ldots < x_{n,} y_n >\}$

Supervised Learning

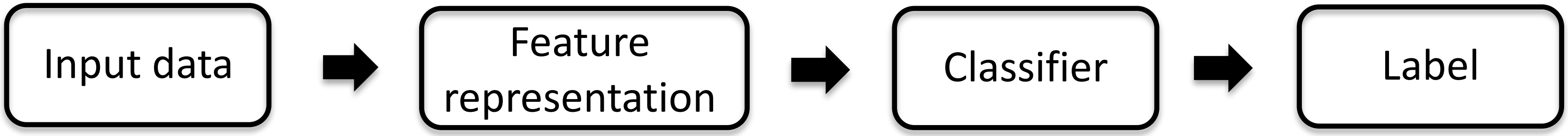
- Regression
  - A target function maps X onto **continuous real values** Y.



- Classification
  - A target function maps X onto **discrete class labels** Y.



Overview of general classification tasks



Input data ➡ Feature representation ➡ Classifier ➡ Label

A vector of numbers

$\vec{x} = <a_1, a_2, \ldots, a_n>$

…that represent attributes of the example, like fundamental frequency, or amplitude.

- Decision Tree

- Nearest Neighbor

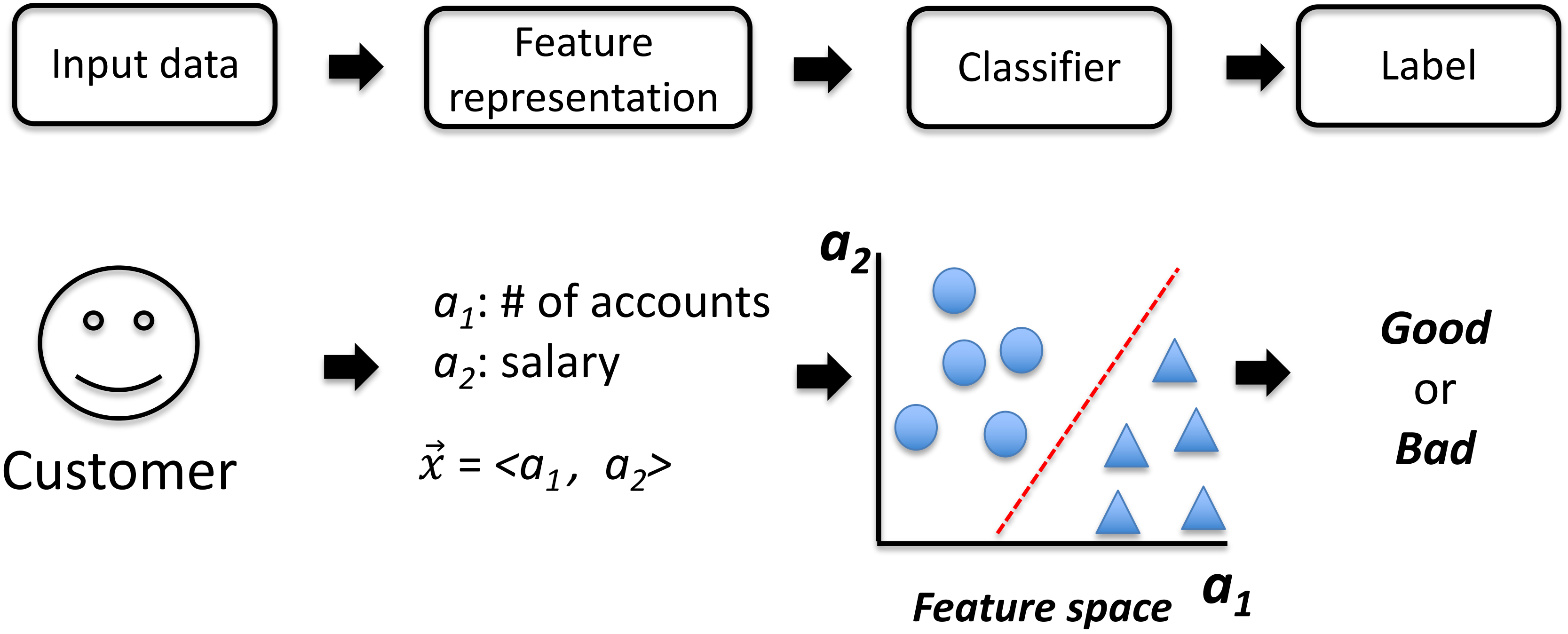
- Neural Networks

“Cat image”

“Piano sound”

Overview of general classification tasks

- Example: Classifying a customer to ***Good*** or ***Bad***



Input data → Feature representation → Classifier → Label

Customer

a_1: # of accounts

a_2: salary

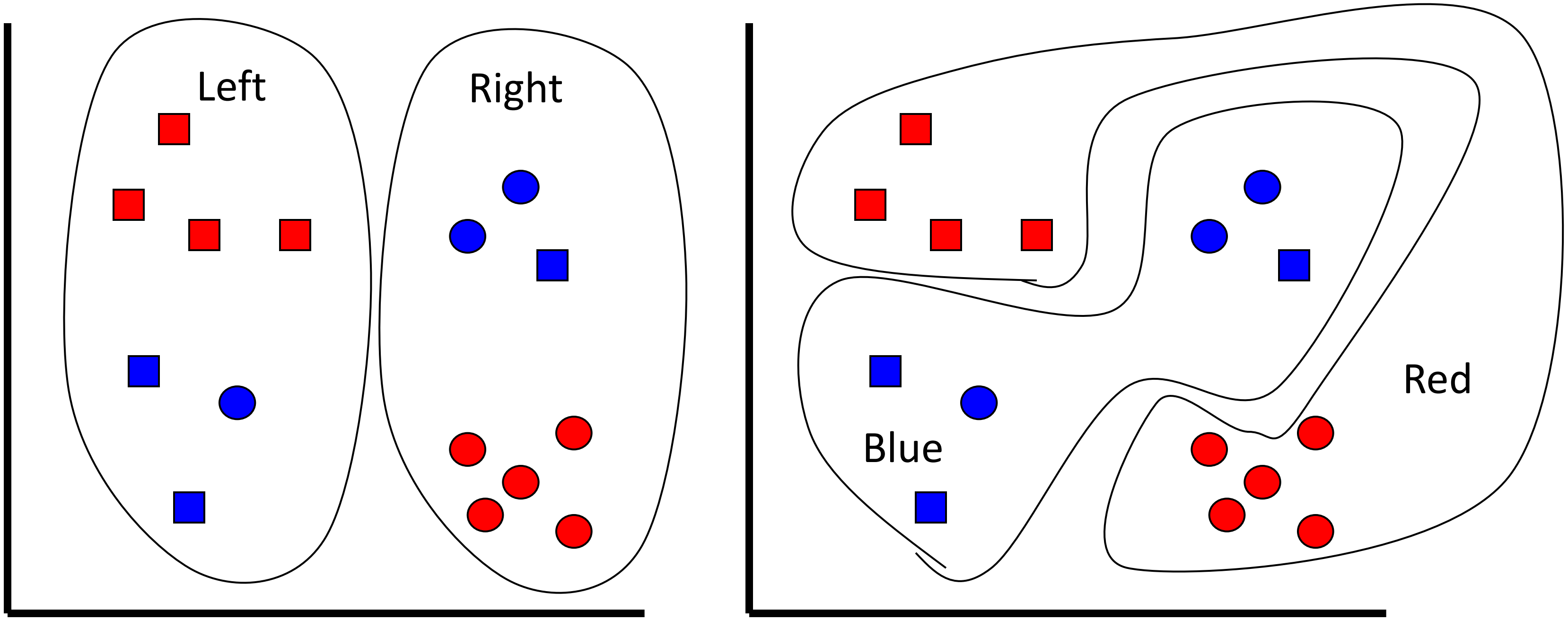
$\vec{x} = <a_1,\ a_2>$

Feature space

Good
or
Bad

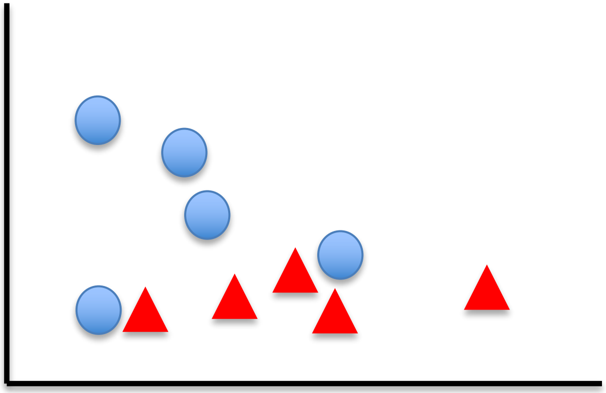
Different Classifiers

- Different classifications need different classifiers.

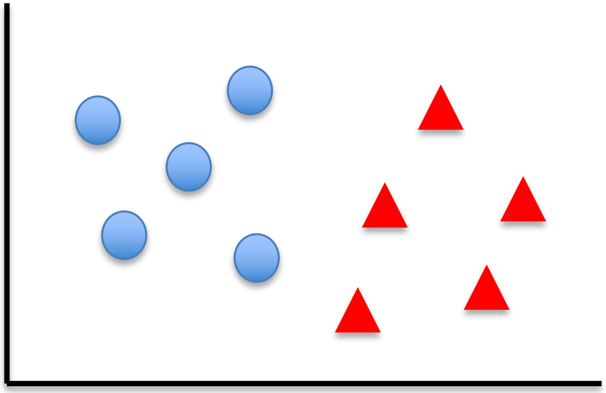


Feature selection is important

- How things cluster depend on what you are measuring.

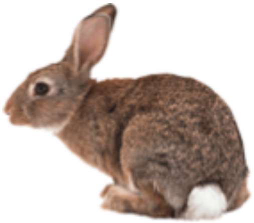


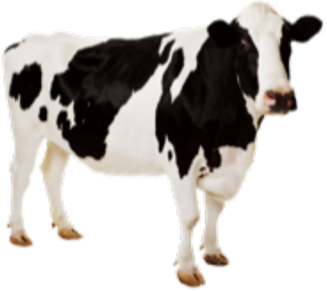
Bad feature representations

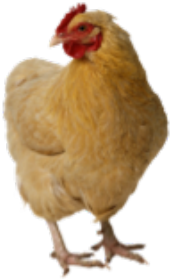


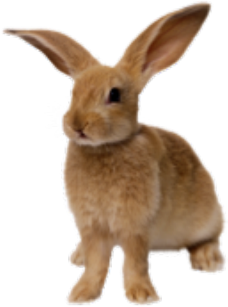
Good feature representations

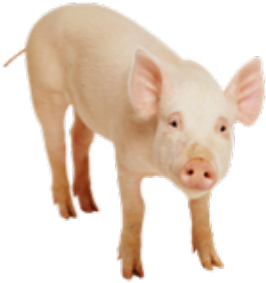
Which of these go together?

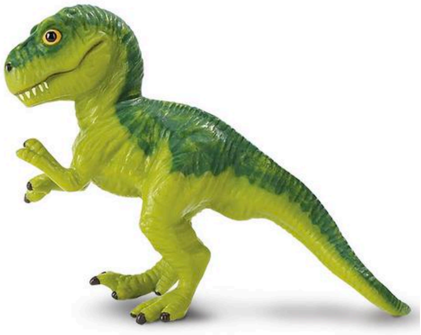


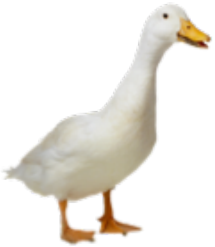


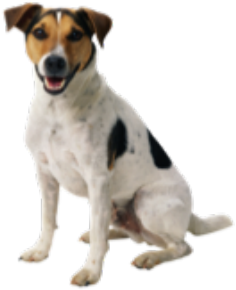












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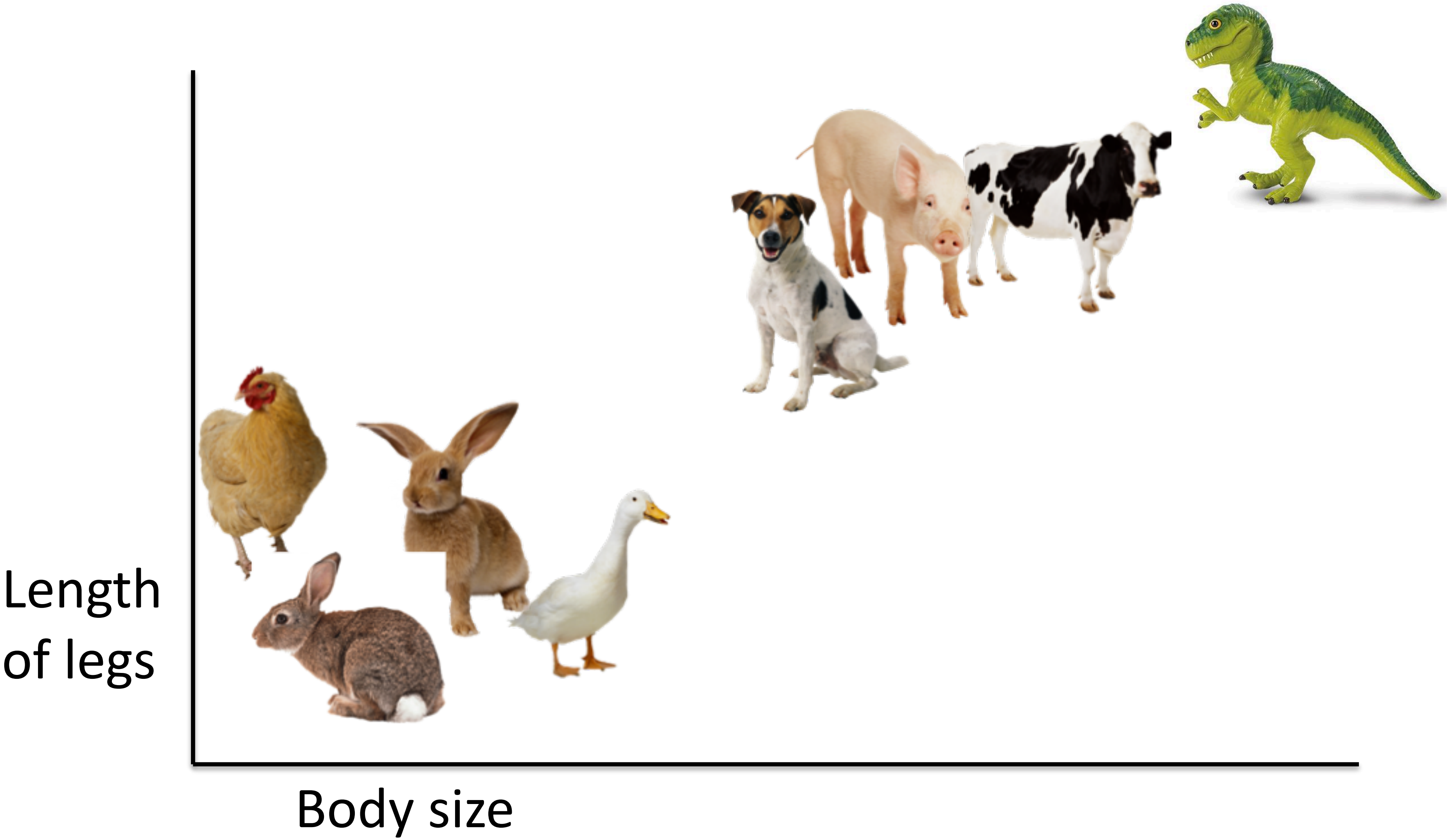

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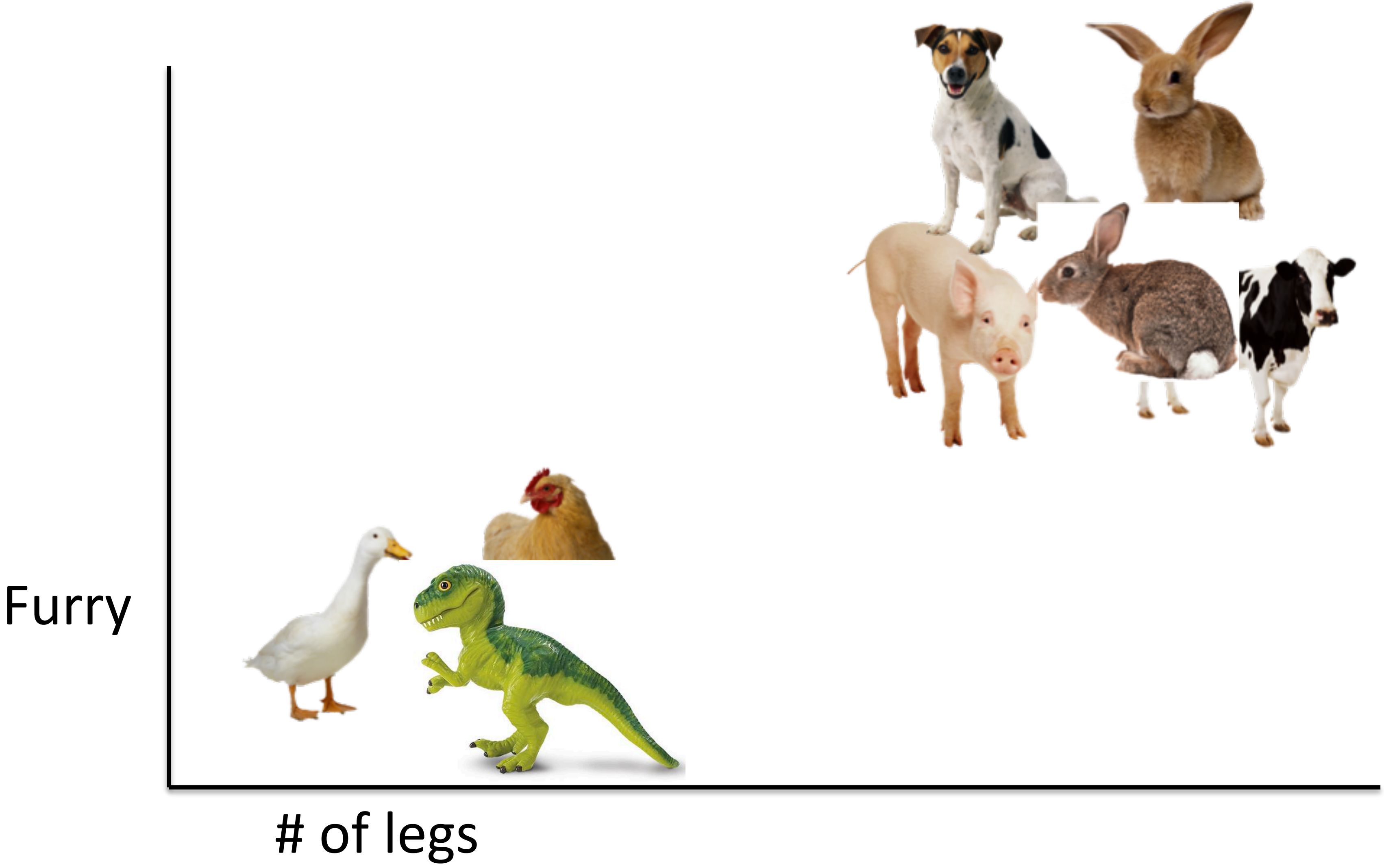
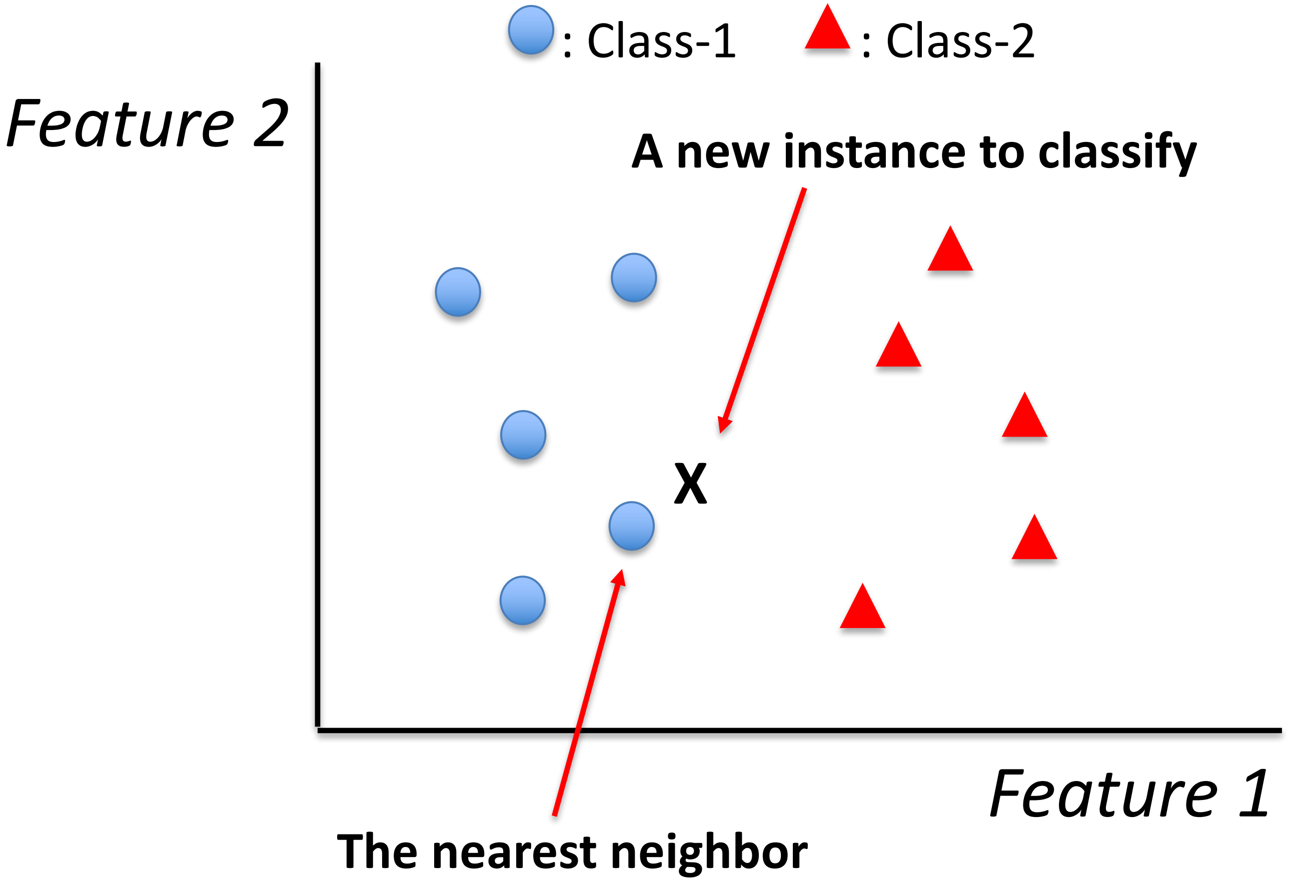


Nearest Neighbor (NN) Classifier

- When you see a new instance x to classify, find **the most similar training example** and assign its label to the instance.

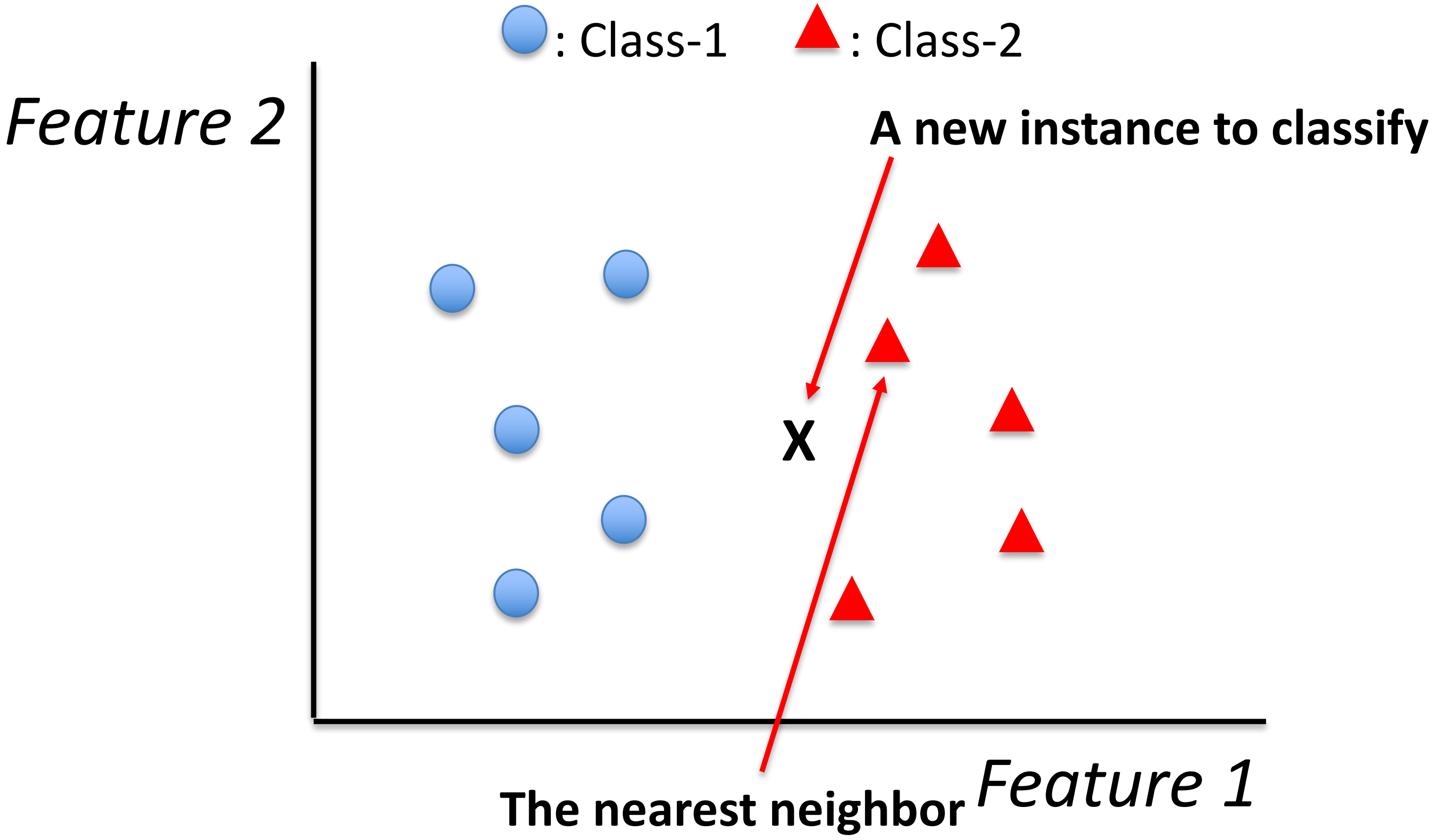
- How do you tell what things are similar?
  1. Extract proper features.
  2. Measure distance / similarity in the feature space.

Nearest Neighbor (NN) Classifier



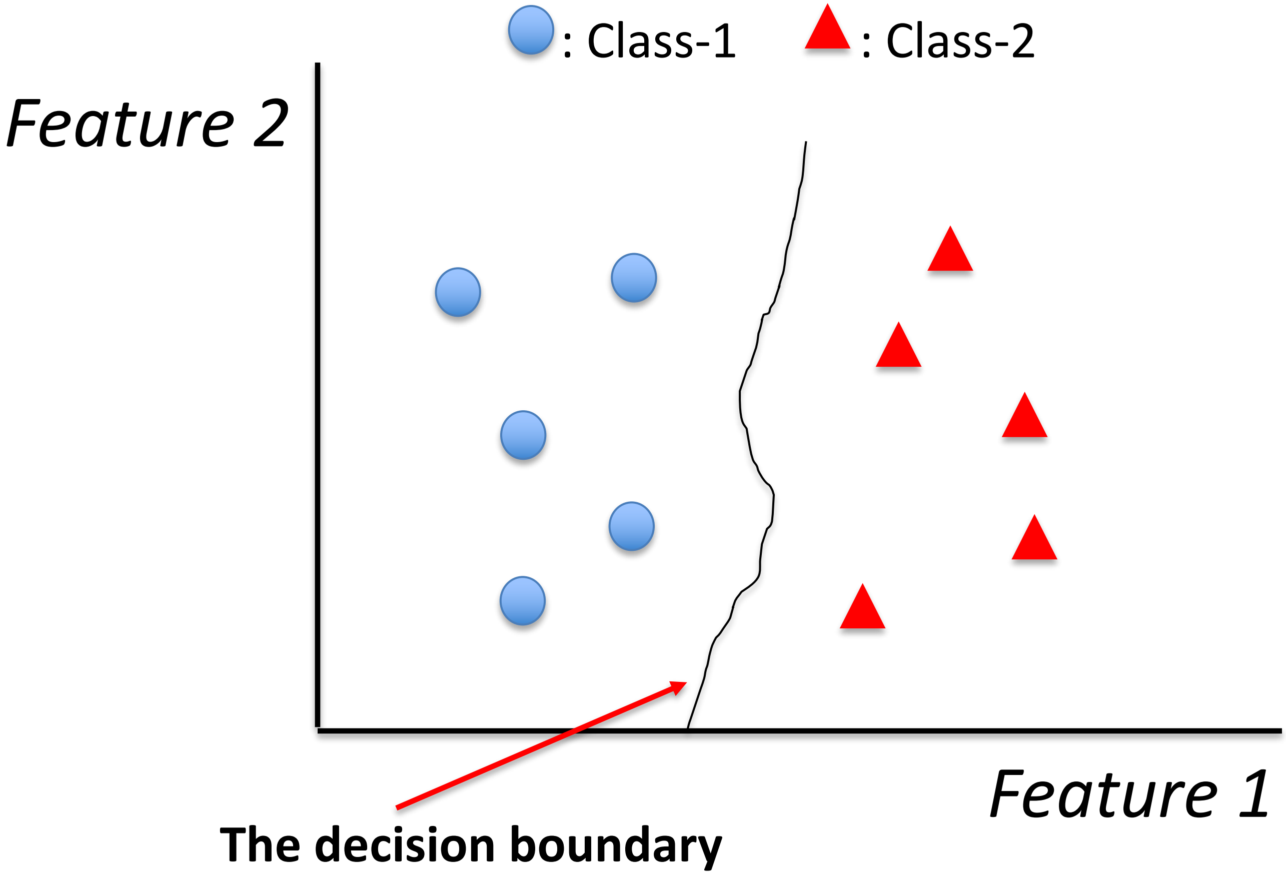
X is classified into class-1

Nearest Neighbor (NN) Classifier



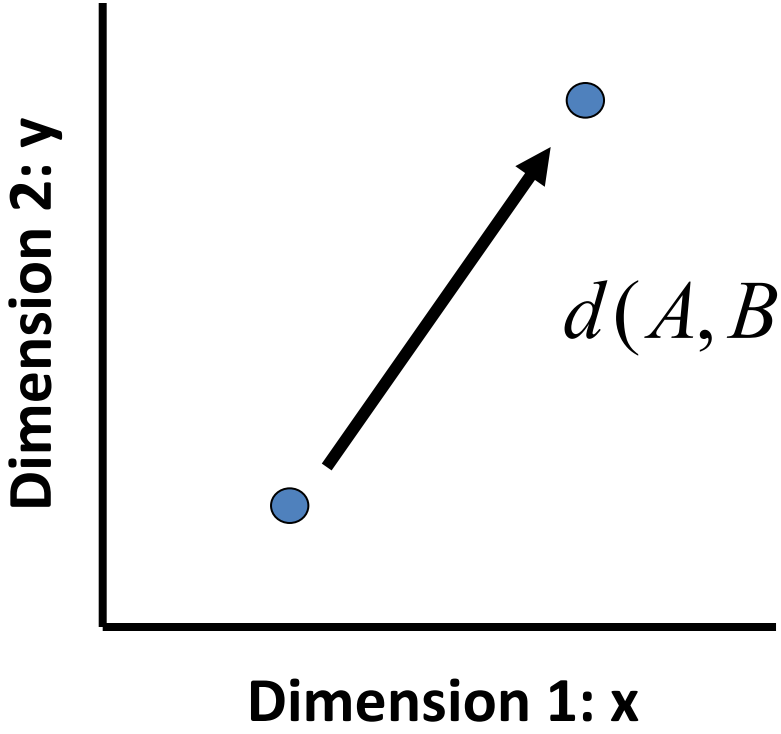
X is classified into class-2

Nearest Neighbor (NN) Classifier



How do we measure distance?

- Euclidian distance
  - – what people intuitively think of as “distance”



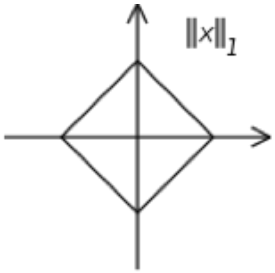
$$d(A,B) = \sqrt{(a_x - b_x)^2 + (a_y - b_y)^2}$$

L^p norms

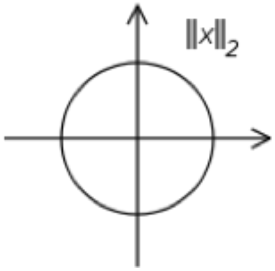
- L^p norms are all special cases of this function:

$$d(\vec{x},\vec{y}) = \left[\sum_{i=1}^{n} | x_i - y_i |^p \right]^{1/p}$$

p changes the norm



L^1 norms = Manhattan Distance: *p=1*



L^2 norms = Euclidean Distance: *p=2*

Cosine Similarity

- Measure of similarity between two vectors
  - Range from -1 (opposite) to 1 (same)
  - Cosine distance = 1 – cosine similarity

- Cosine similarity between vector *A* and *B:*

$$sim(A, B) = \frac{A \cdot B}{\|A\|\|B\|}$$

$$A \cdot B = \sum_{i=1}^{n} A_i B_i \qquad \|A\|\|B\| = \sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}$$

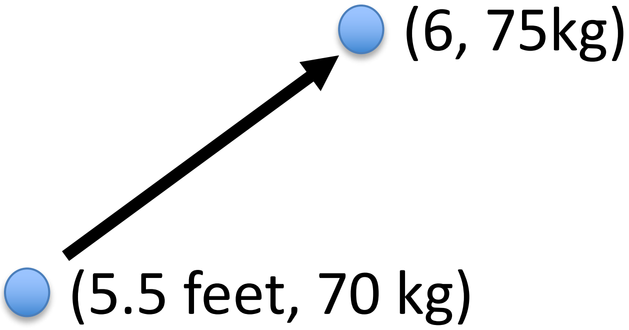
Feature Scaling

- Different scales of features can mislead distance measure.

  E.g., Measuring distance between humans

  - Feature 1: Height (0-7 feet)

  - Feature 2: weight (0-150 kg)

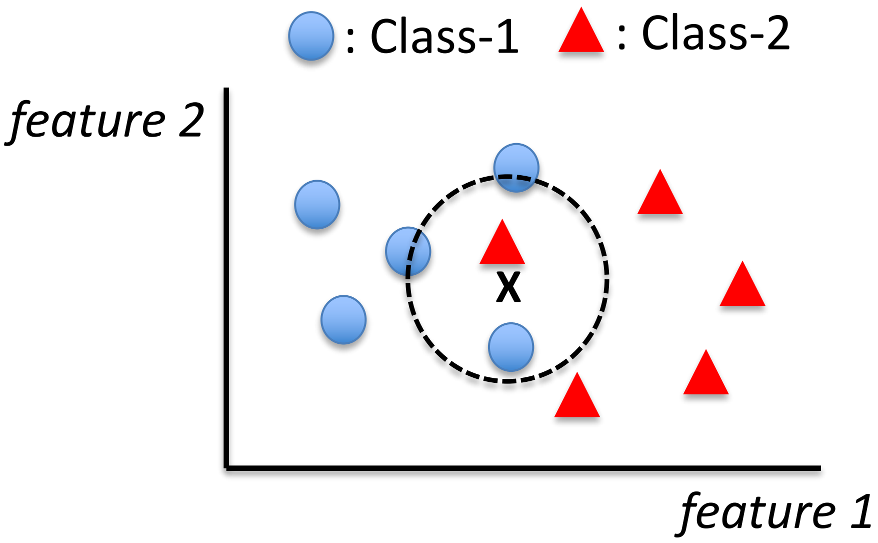


In this Euclidean space, the second feature dominates the distance, which might lead to mis-clustering.

Scaling each feature such that it ranges from 0 to 1 can help.

K-Nearest Neighbor (KNN) Classifier

- Consider multiple neighbors
- Assign most popular label among K nearest neighbors
- More robust to noisy data than NN (k=1)



Considering 4 nearest neighbors (k=4), most popular class is Class-1

Choosing K

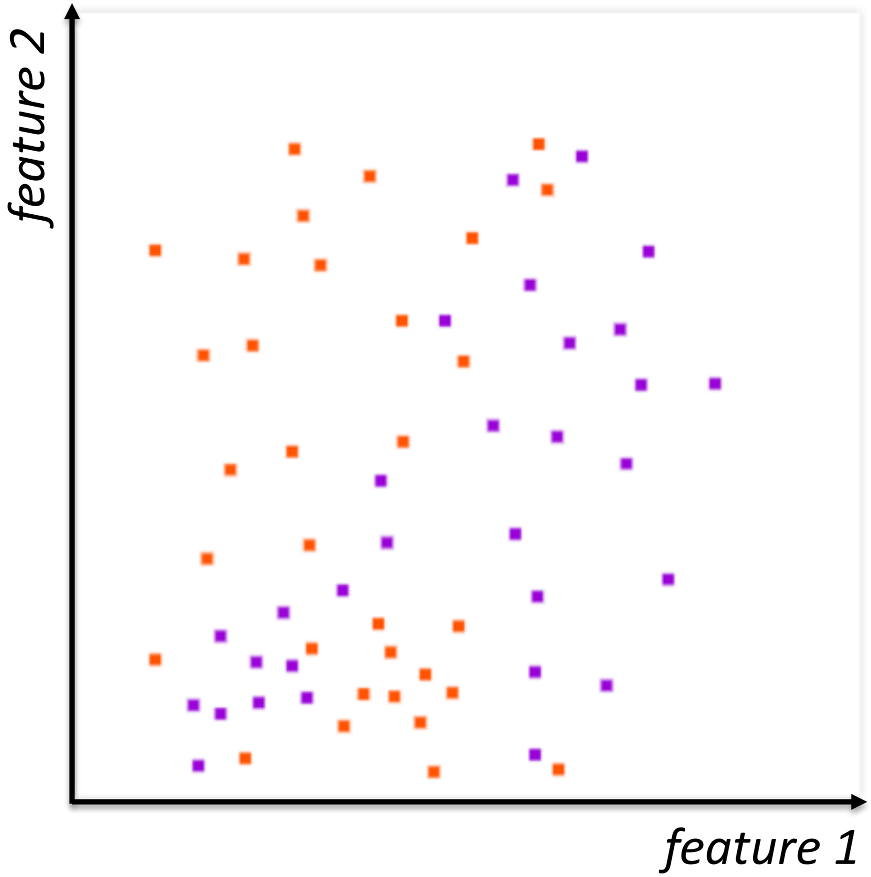
- Making K too small fits the output to the noise in the dataset (overfitting)

- Making K too large can make decision boundaries in classification indistinct (underfitting)

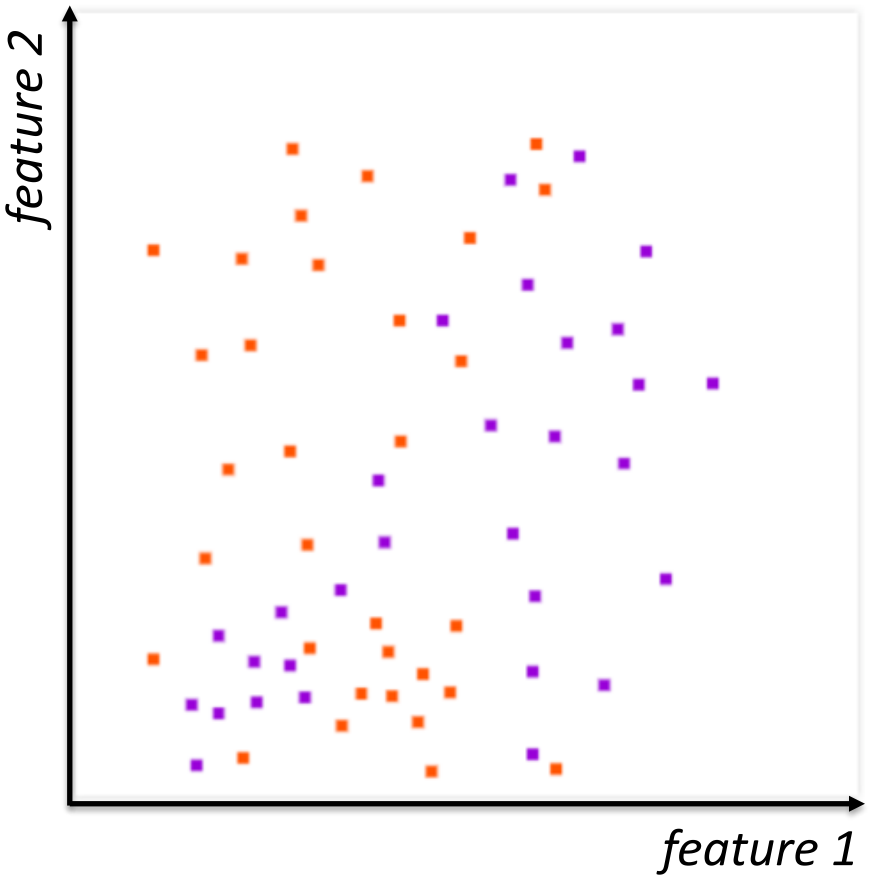
- Choose K empirically using cross-validation

Choosing K

K=1

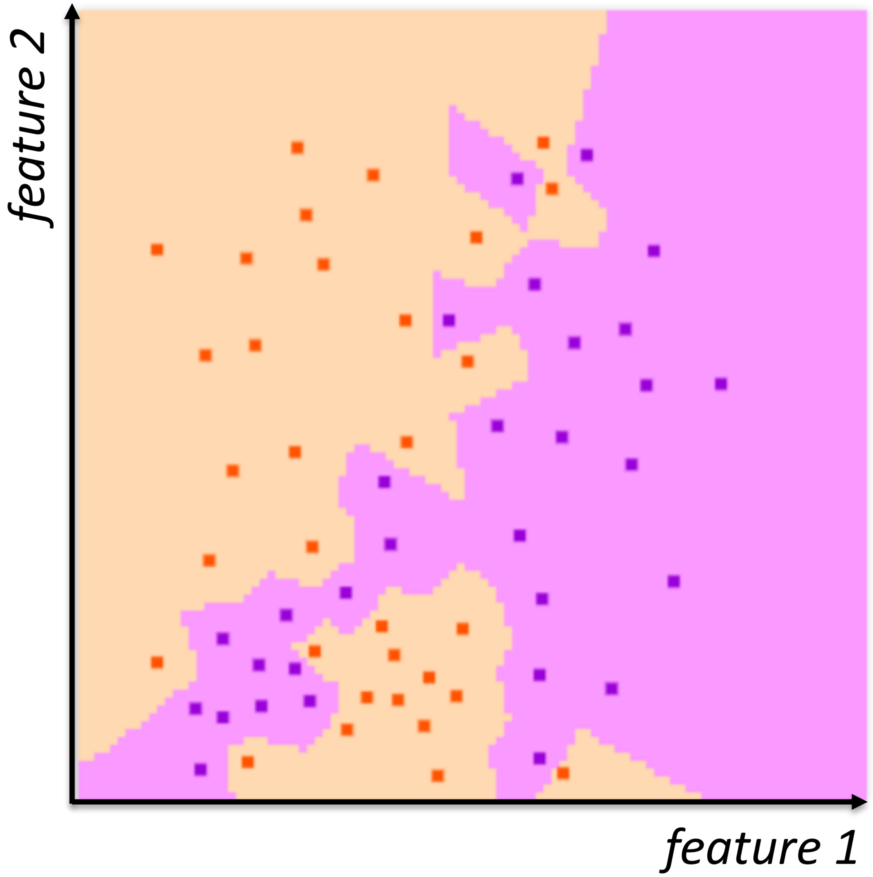


K=20



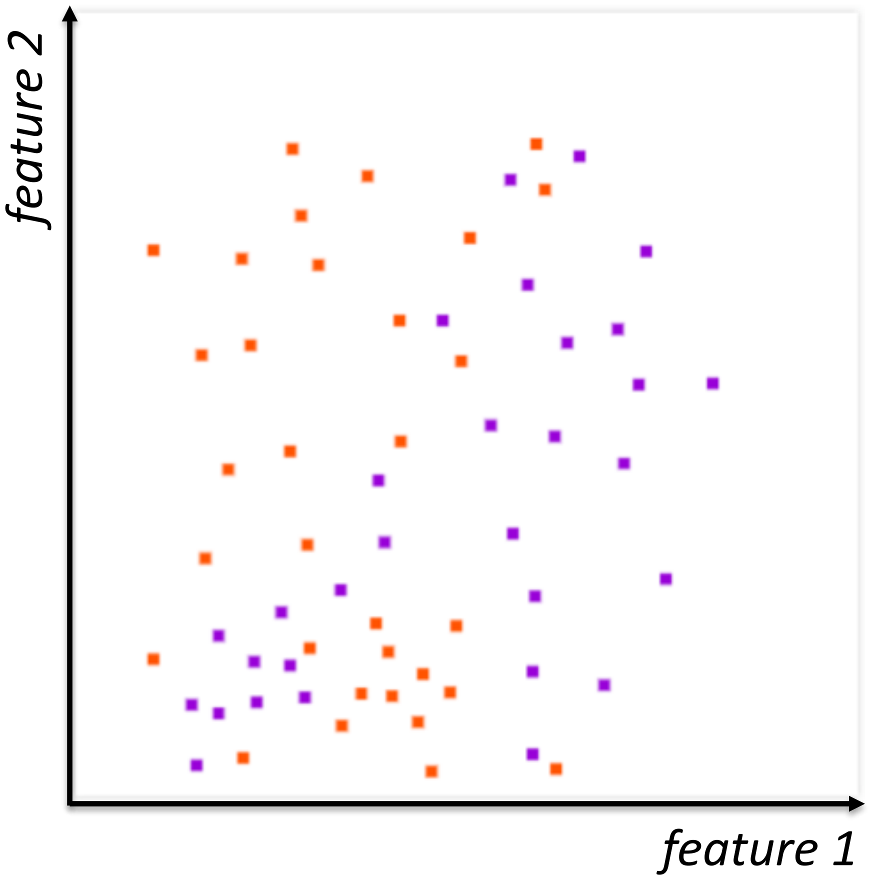
Choosing K

K=1



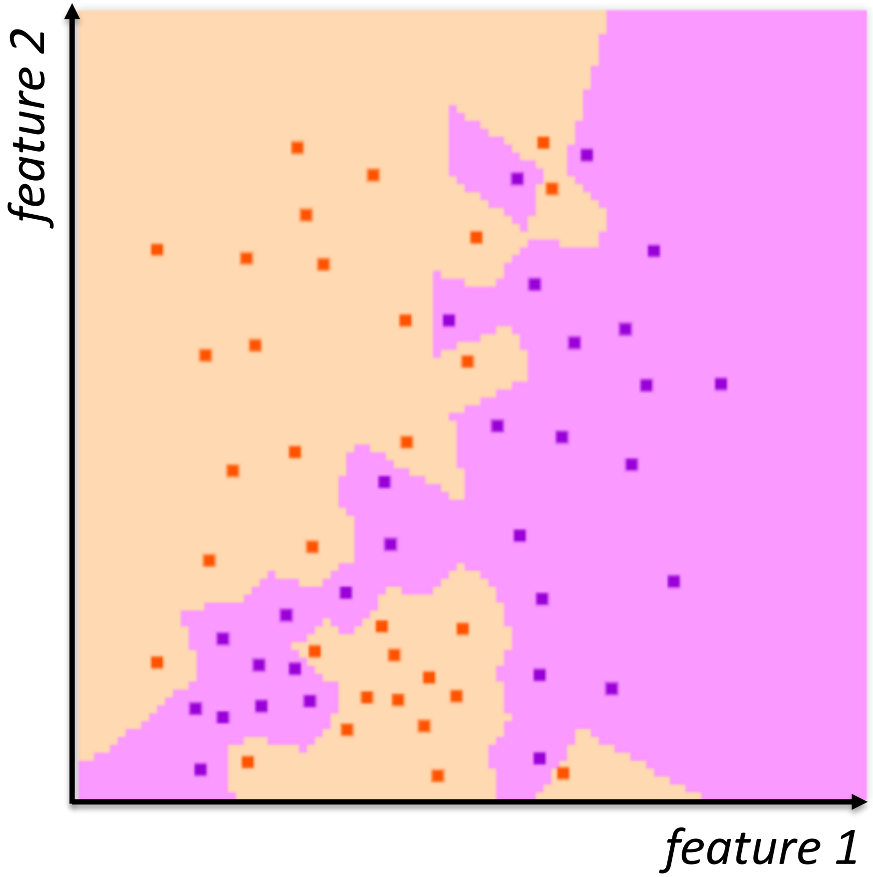
Overfitting

K=20



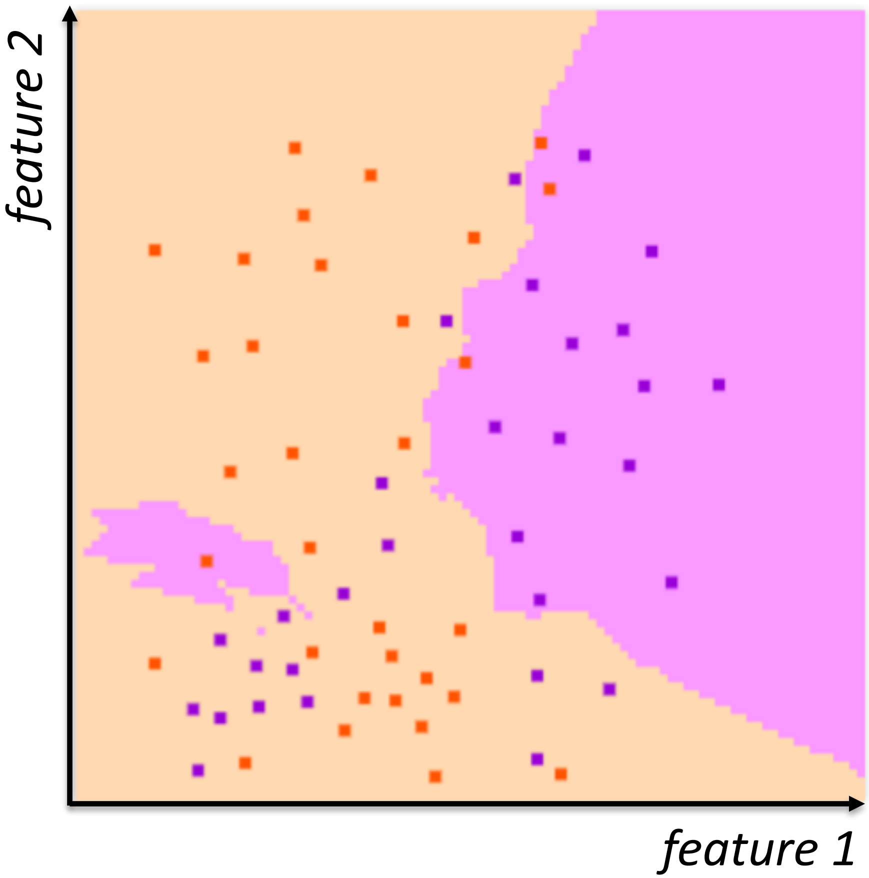
Choosing K

K=1



Overfitting

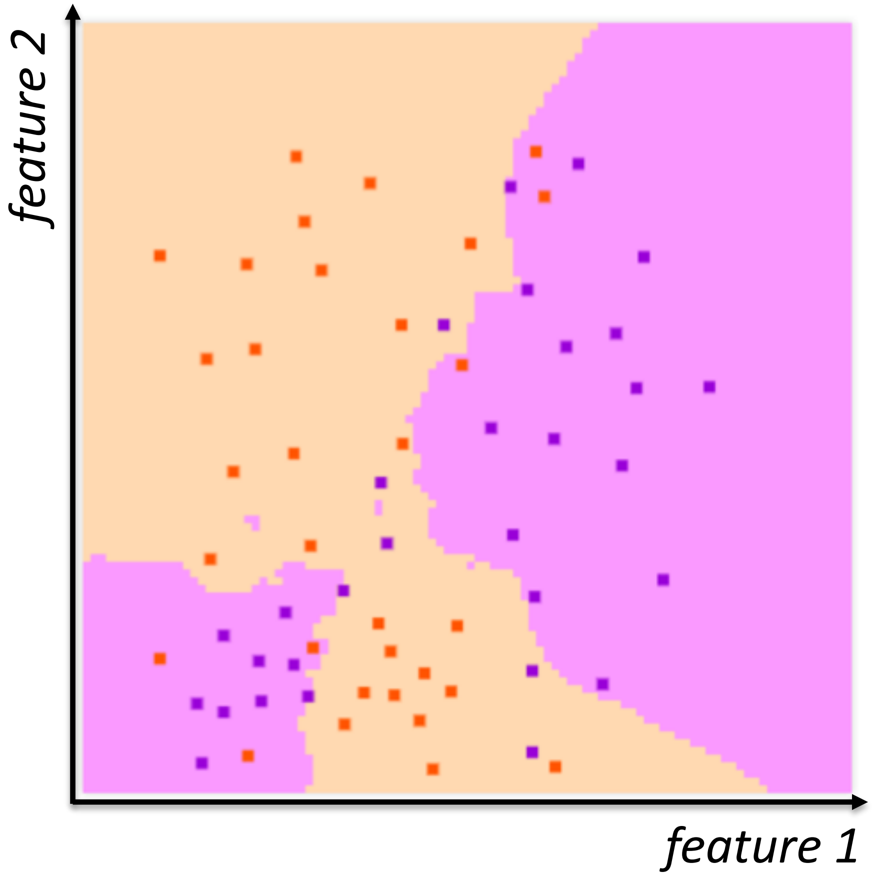
K=20



Underfitting

Choosing K

K=10



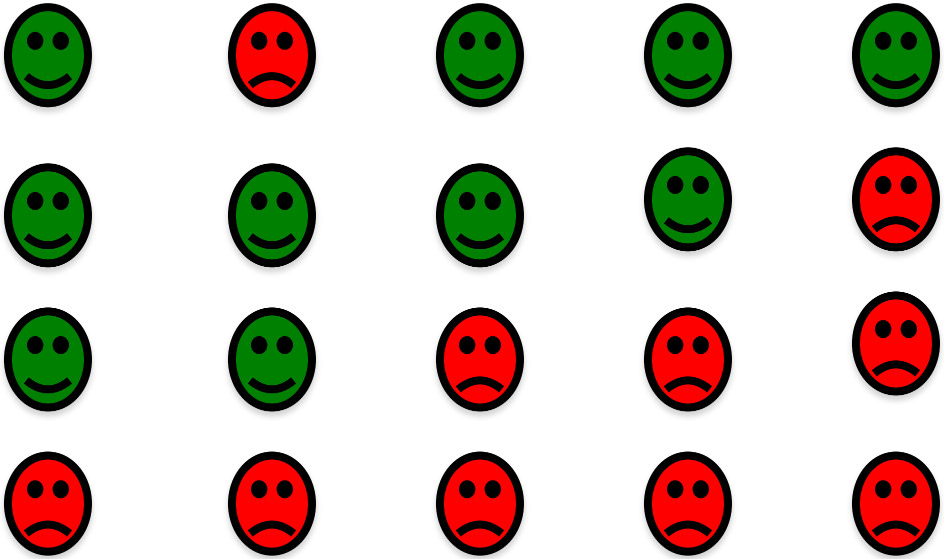
N-fold cross validation

1) Split data into N groups

2) Train on N-1 groups

3) Validate on the Nth

4) Rotate, repeat



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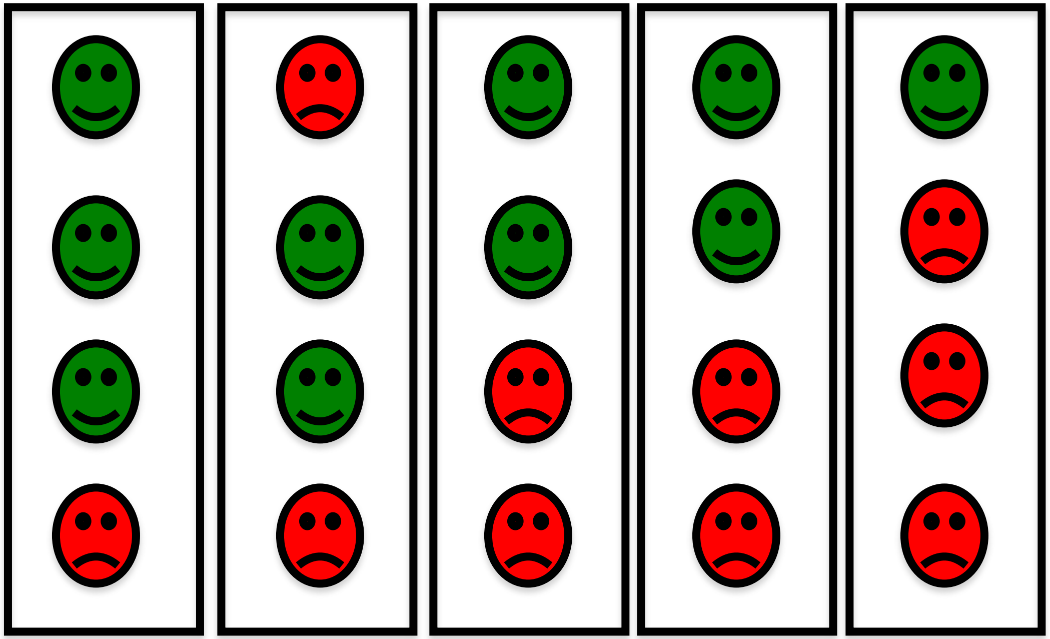

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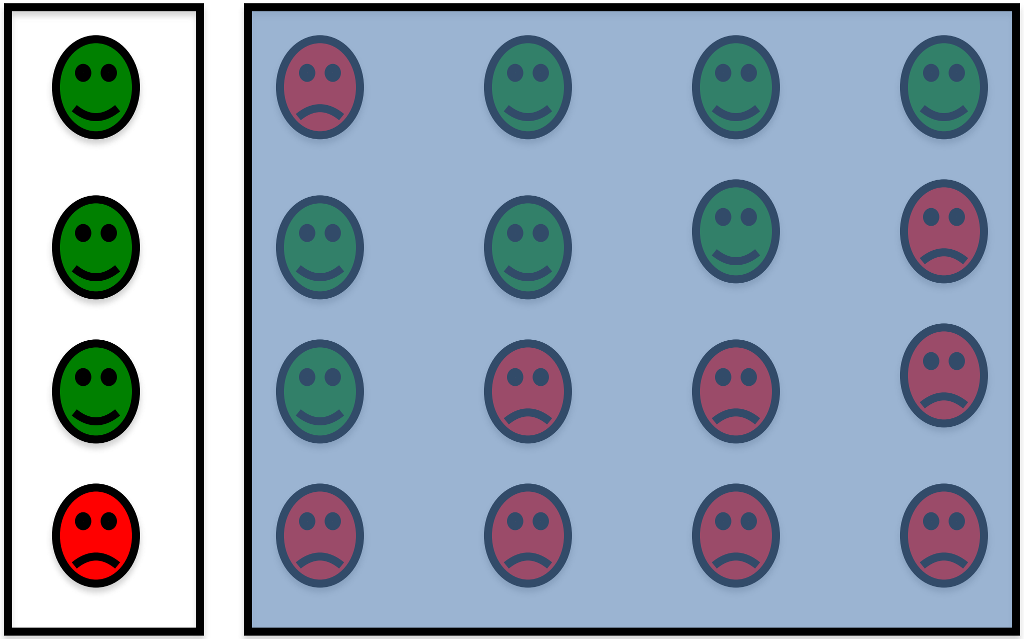

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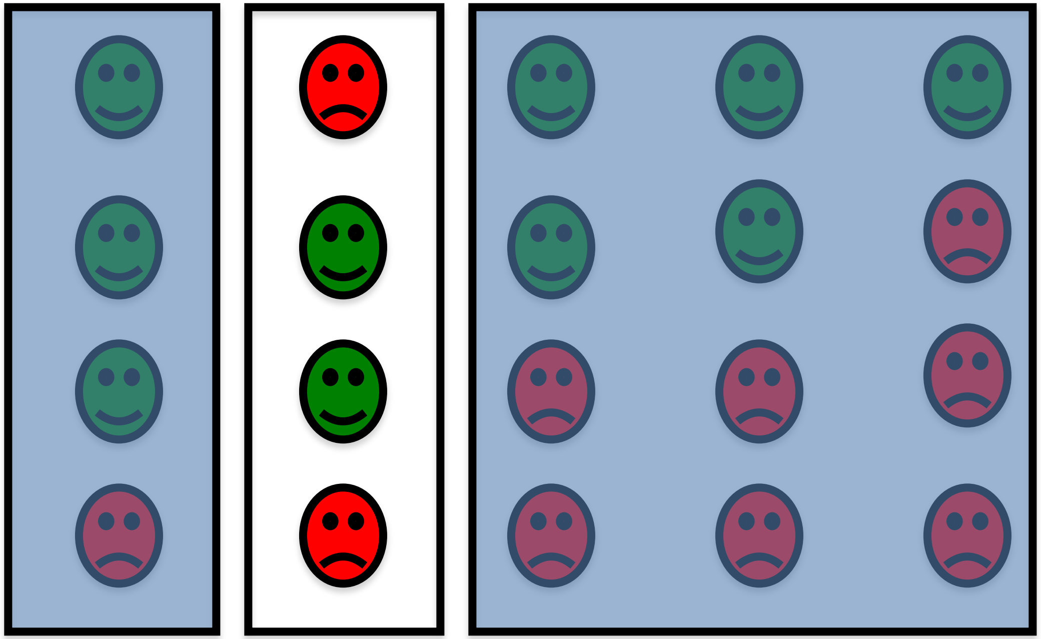

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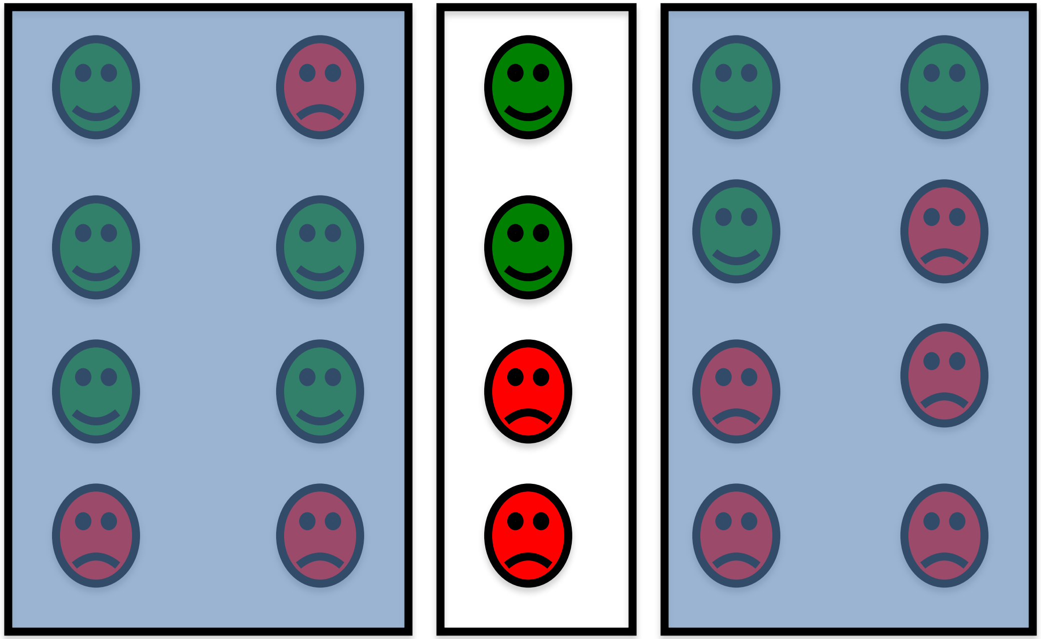


Evaluation: Classification accuracy

- Evaluation on a dataset that has NOT been used in model building.
- Classification accuracy
  - # of correct classifications / total # of examples
- Example: comparing two classifiers
  - Classifier 1: 80% of accuracy
  - Classifier2: 78% of accuracy
  - Which one would you pick for your system?
- Classification accuracy might hide the details of the performance of your model.

Evaluation: Confusion matrix

- Confusion matrix gives you a better understanding of the behavior of your classifier.

Predicted label

True label

	Piano	**violin**	**Guitar**
Piano	**19**	**0**	**1**
violin	**0**	**15**	**5**
Guitar	**1**	**3**	**16**

Evaluation: Confusion matrix

- Confusion matrix gives you a better understanding of the behavior of your classifier.

Predicted label

True label

	Piano	**violin**	**Guitar**
Piano	**19**	**0**	**1**
violin	**0**	**15**	**5**
Guitar	**1**	**3**	**16**

Classification accuracy:
50/60 = 83%

Predicted label

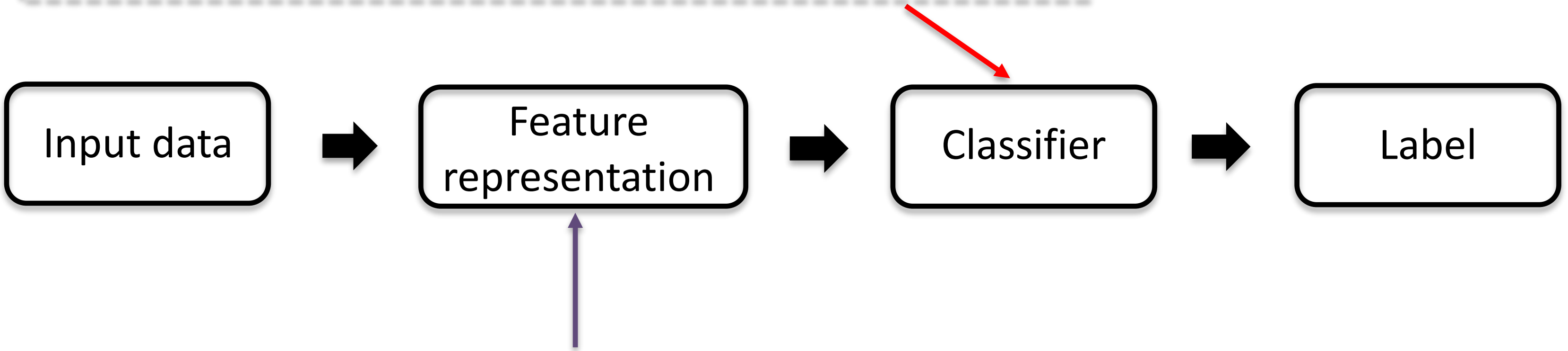
True label

	Piano	**violin**	**Guitar**
Piano	**20**	**0**	**0**
violin	**7**	**11**	**2**
Guitar	**1**	**0**	**19**

Classification accuracy:
50/60 = 83%

Now that we know..

- How to build a KNN classifier
- How to evaluate it

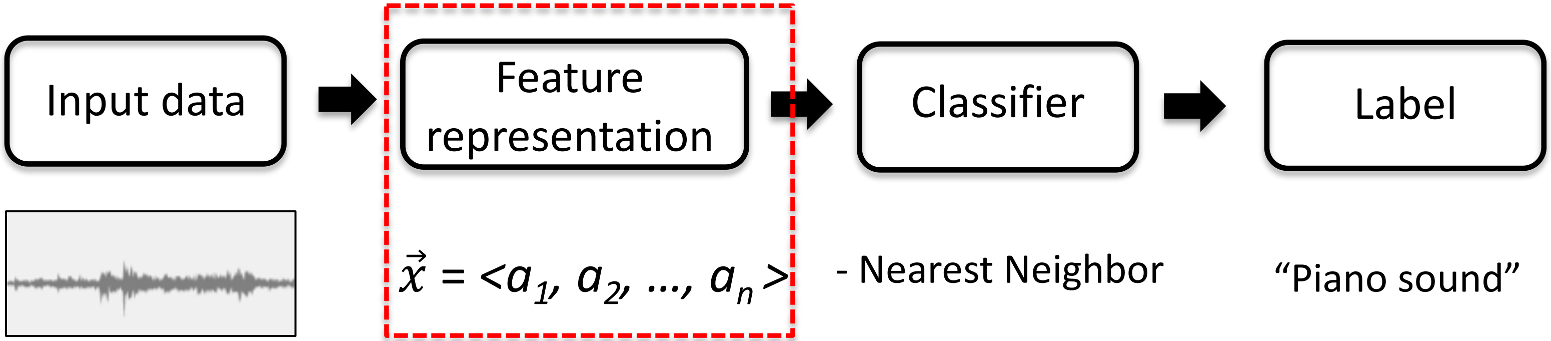


Input data → Feature representation → Classifier → Label

- We need to learn how to extract feature representations from audio input to build audio classification model.

AUDIO EVENT CLASSIFICATION

Audio event classification



Input data → Feature representation → Classifier → Label

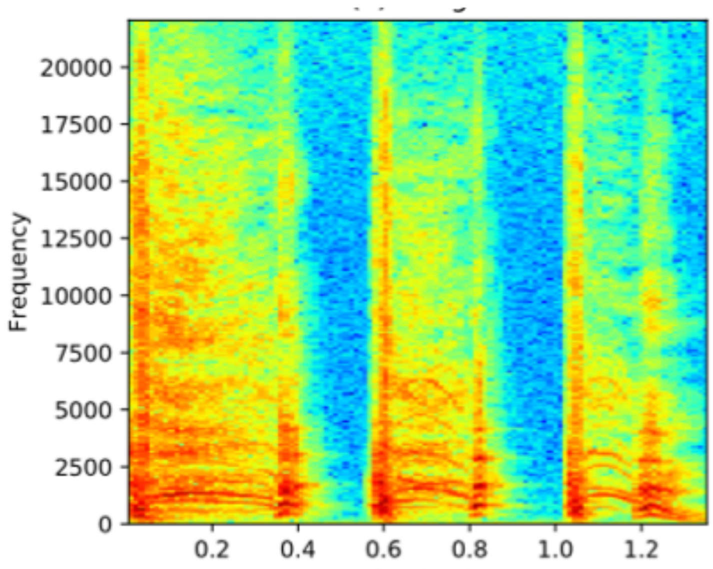
$\vec{x} = <a_1, a_2, \ldots, a_n>$

- Nearest Neighbor

“Piano sound”

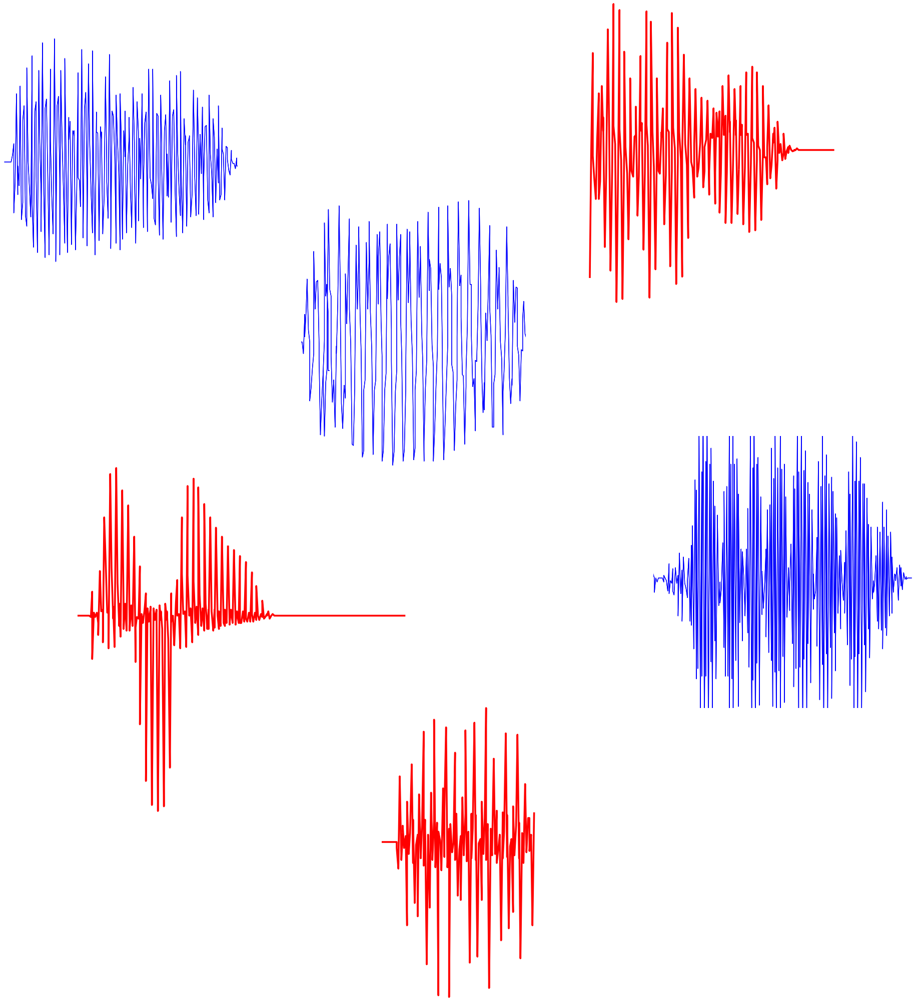
We need to convert waveform to feature representations to feed in a classifier.

- We have already learned one of feature representations: Spectrogram



Why not use the waveform as a feature?

- It is hard to find meaningful patterns



Why not use the waveform as a feature?

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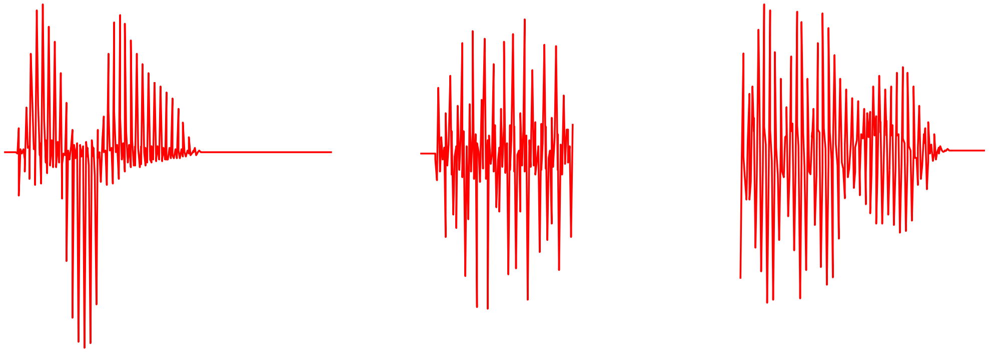
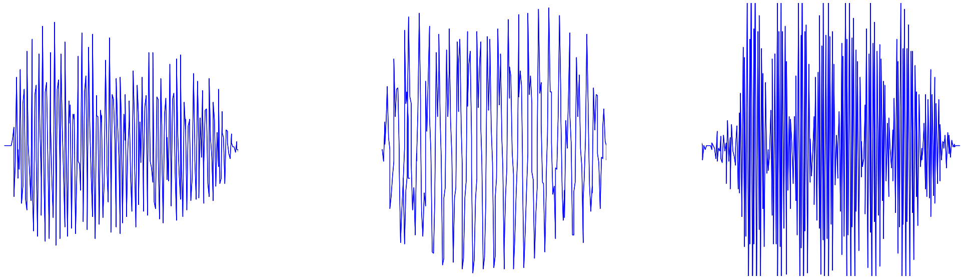




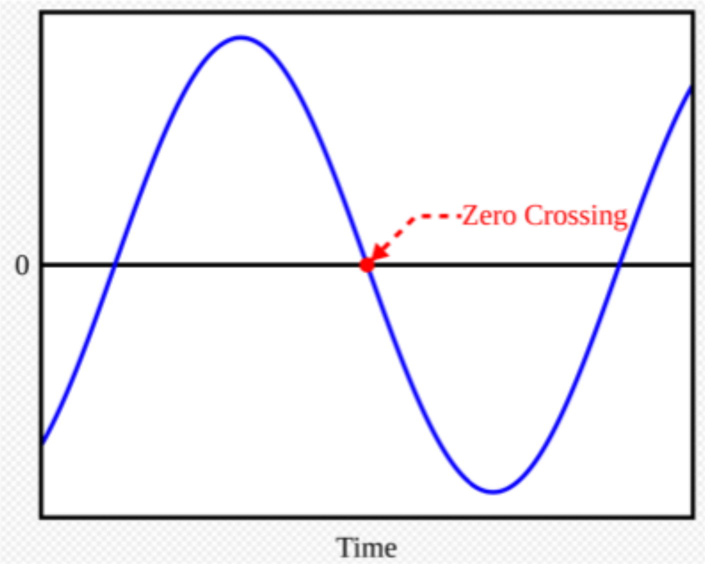
Why not use the waveform as a feature?

- It is hard to find meaningful patterns
  - It needs a very powerful model such as deep neural networks which require millions of training data.

- Waveform is too big.
  - 1 second of audio at 44.1kHZ ➔ 44,100 values

Commonly used audio features

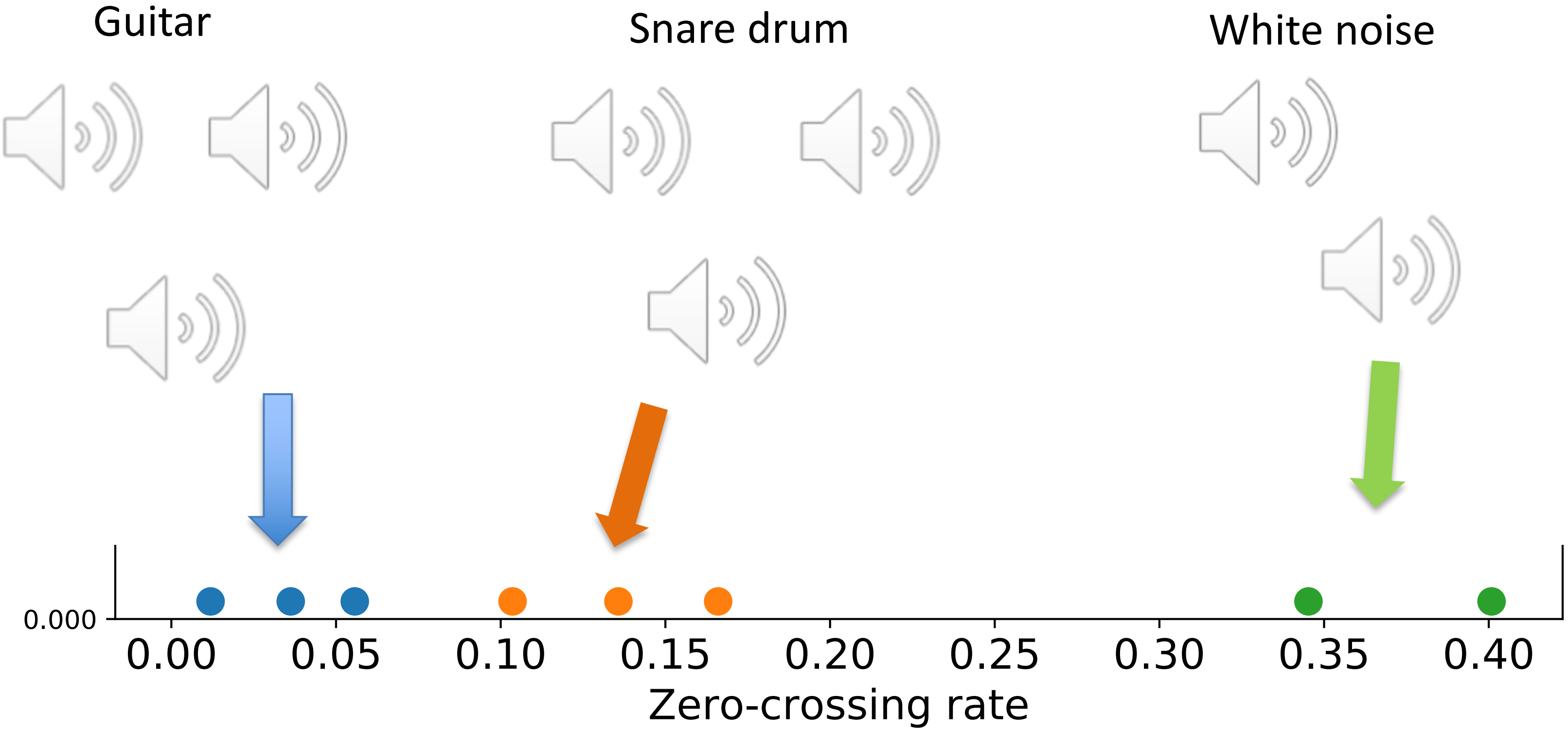
- Zero-crossing rate
  - Time-domain feature
  - Rate of sign changes in a signal
  - Low for harmonic sounds, high for noisy sounds



* Figure: https://en.wikipedia.org/wiki/Zero_crossing

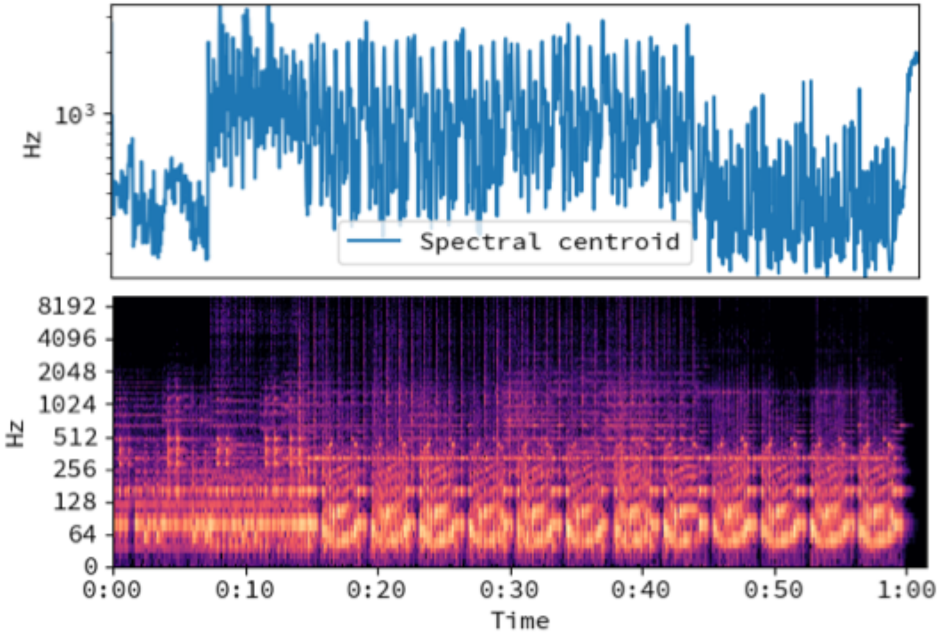
Commonly used audio features

- Zero-crossing rate



Commonly used audio features

- Spectral centroid
  - Frequency domain feature
  - The weighted mean of the frequencies in the signal
  - Known as a predictor of the "brightness" of a sound



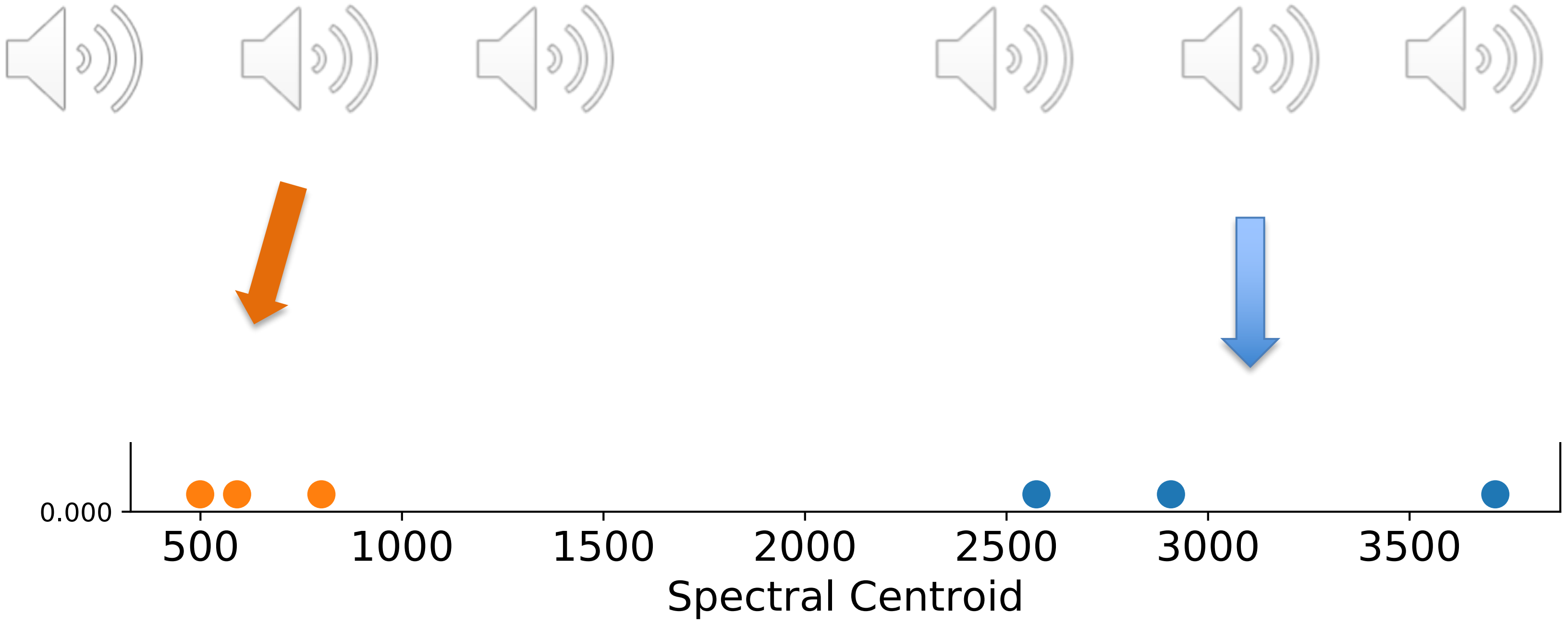
* figure: https://librosa.github.io/librosa/generated/librosa.feature.spectral_centroid.html

Commonly used audio features

- Spectral centroid

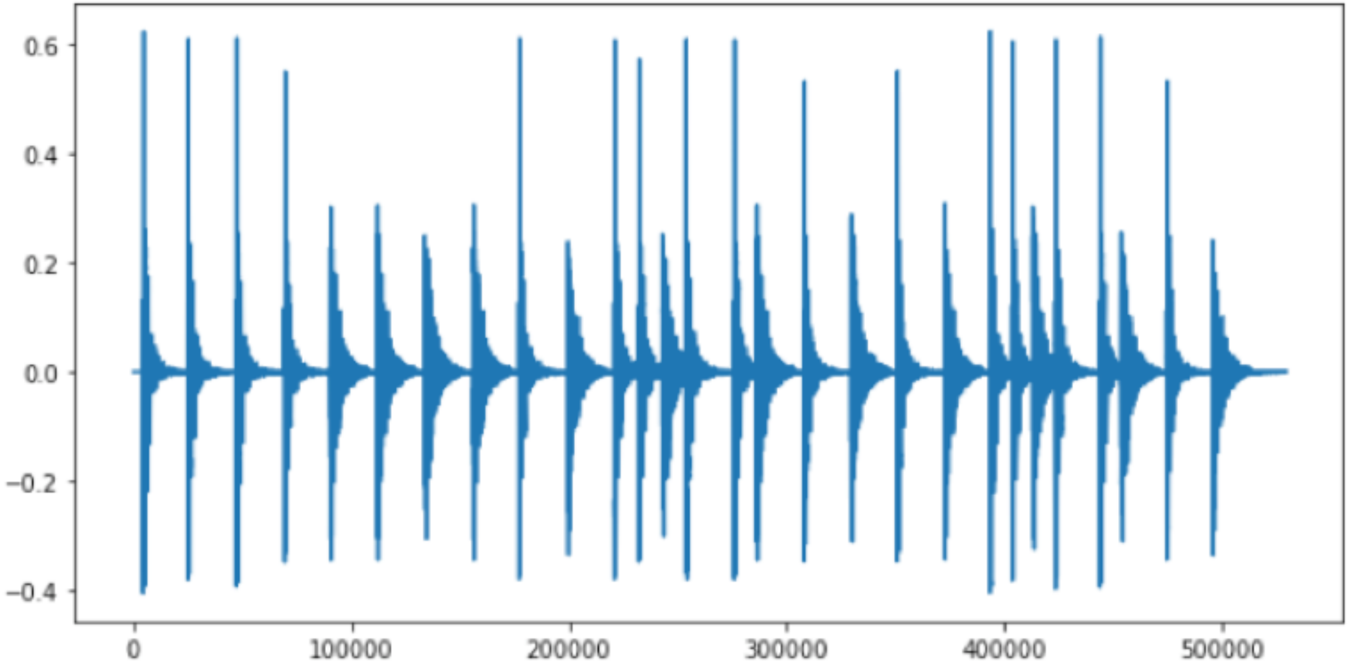
Kick drum

Snare drum



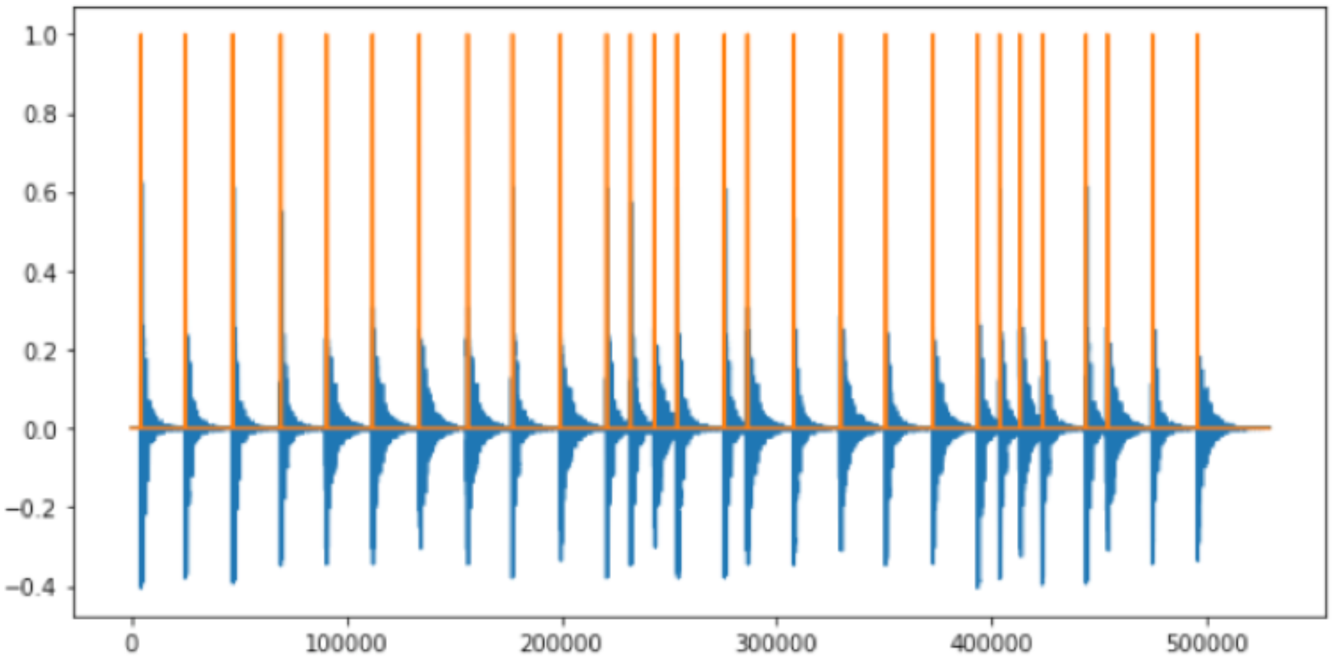
Automatic drum transcription

- Let’s build a drum transcription machine only using spectral centroid features



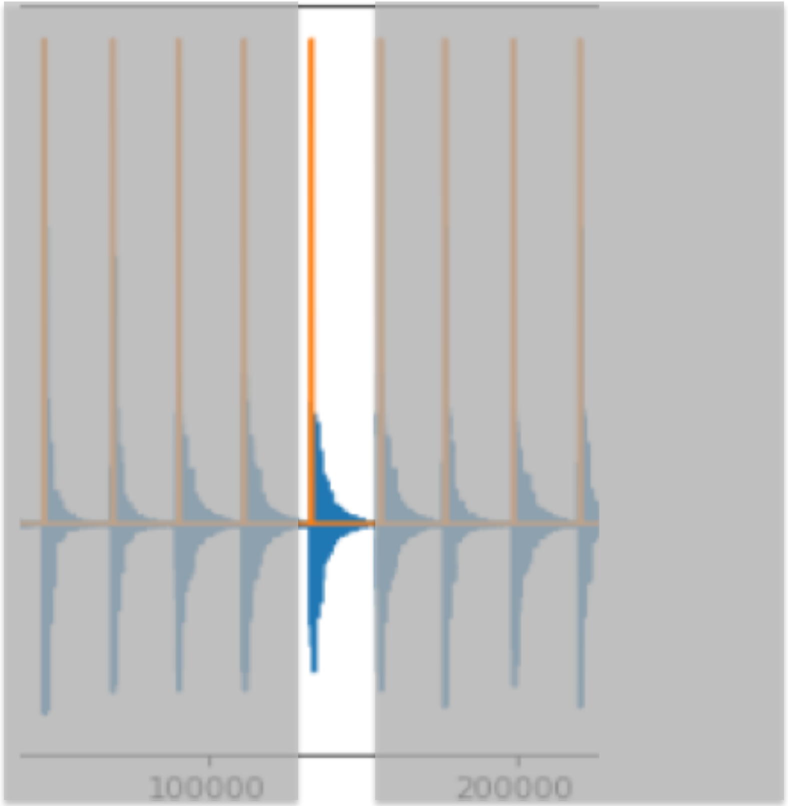
Automatic drum transcription

- Onset detection
  - **librosa.onset.onset_detect**



Automatic drum transcription

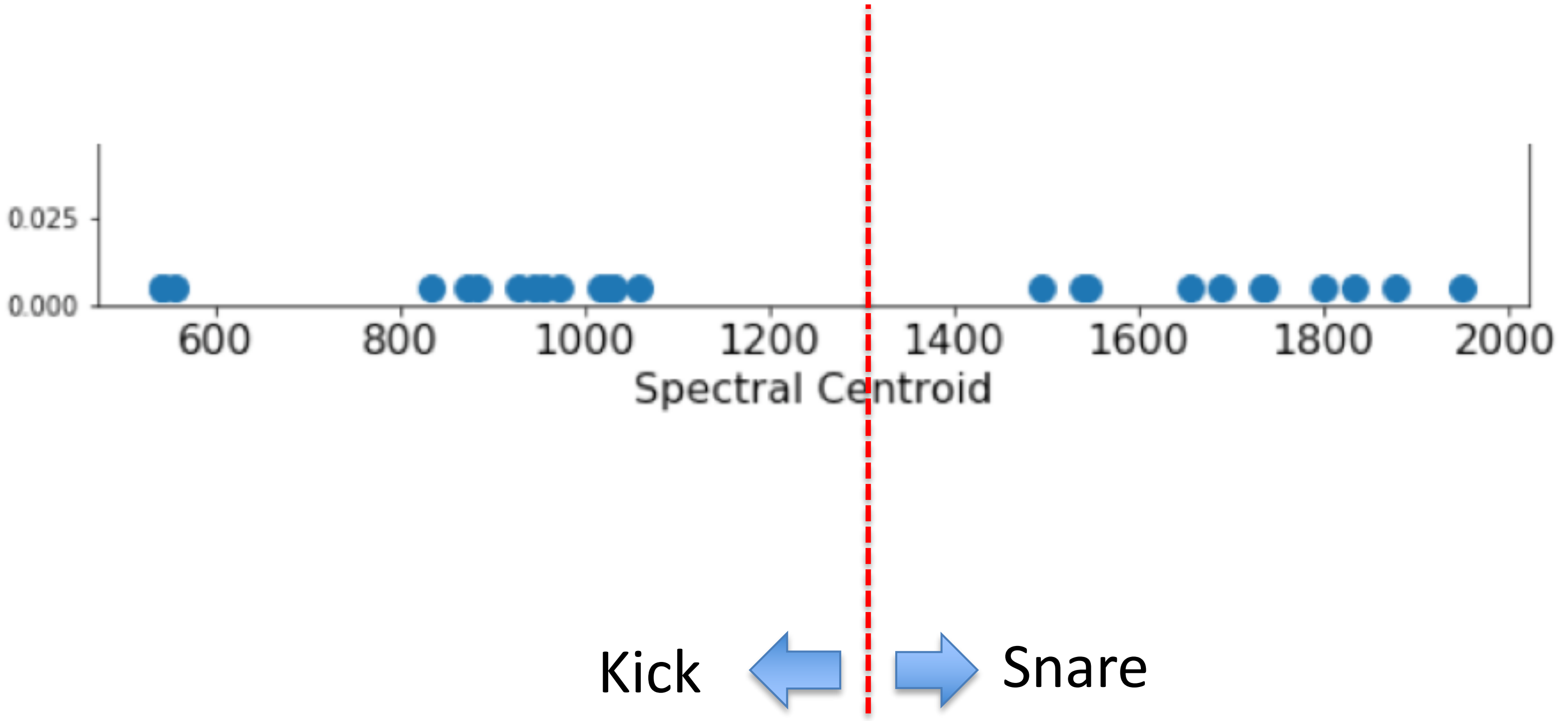
- Segmentation
  - Cutting the recording every *<onset−2048 samples>*



(Onset[t − 1] − 2048 , Onset[t] − 2048)

Automatic drum transcription

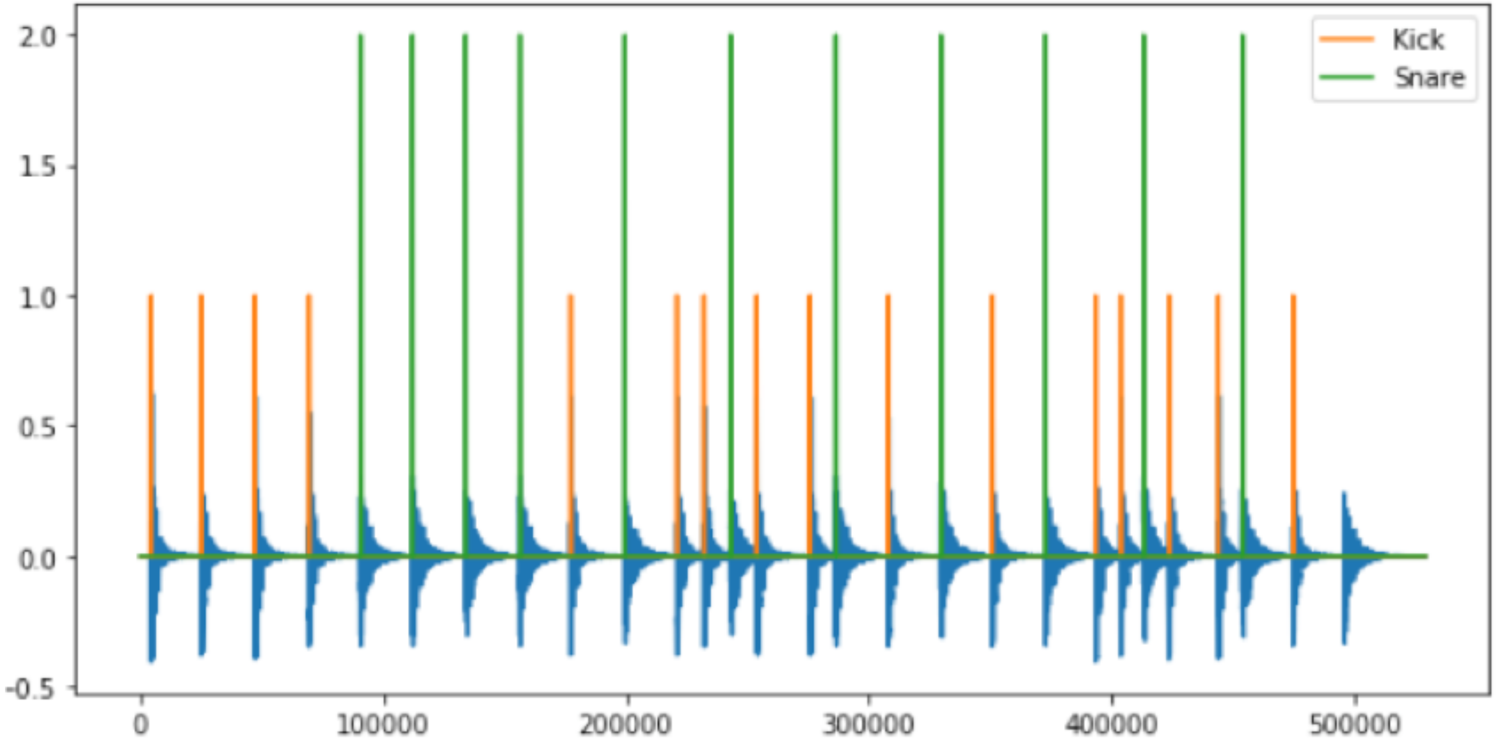
- Extracting spectral centroid from each segment



Kick

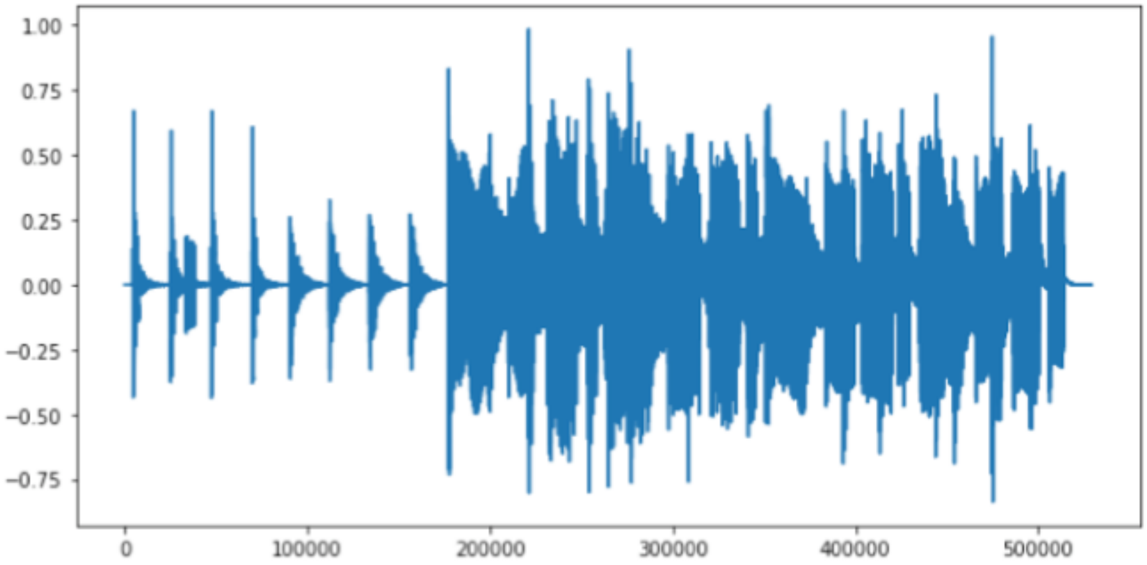
Snare

Automatic drum transcription



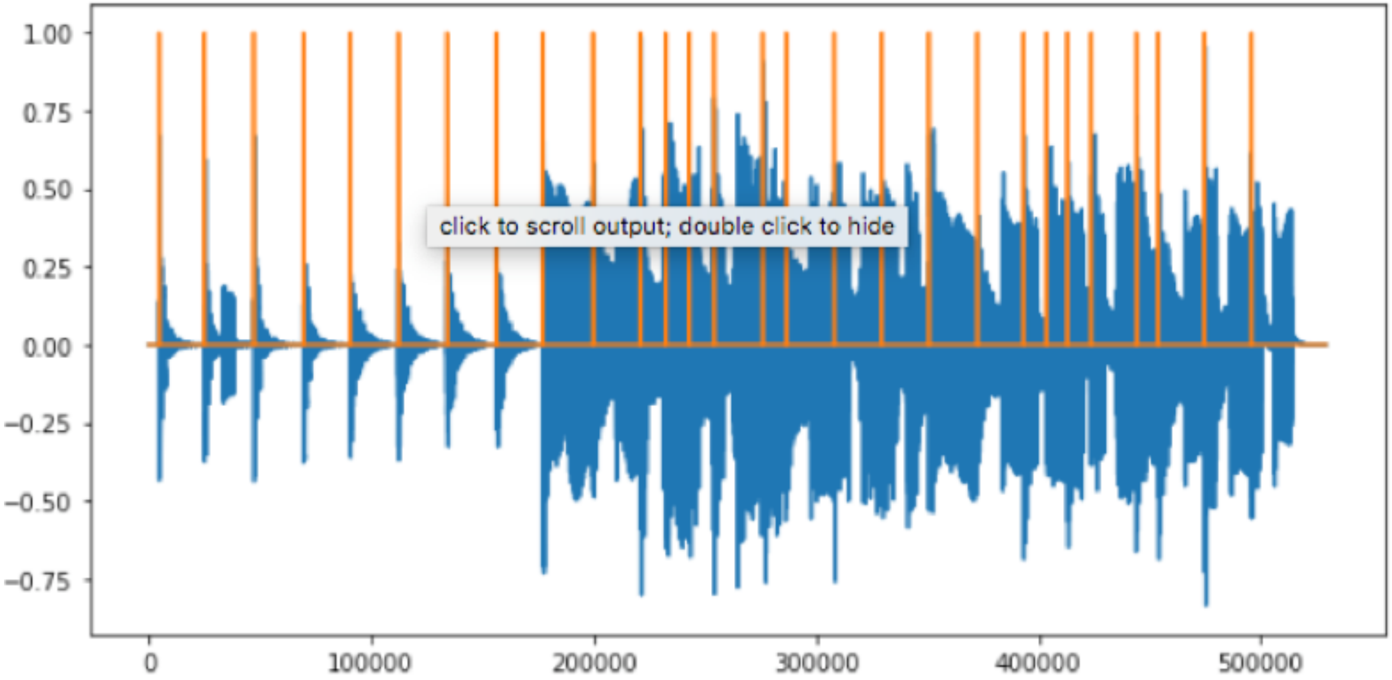
Automatic drum transcription-2

- More challenging example



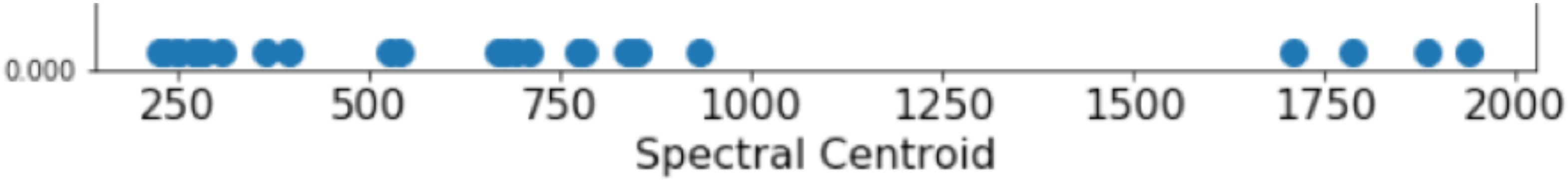
Automatic drum transcription-2

- Onset detection might not work that well on this example, but let's assume we have perfect onset info

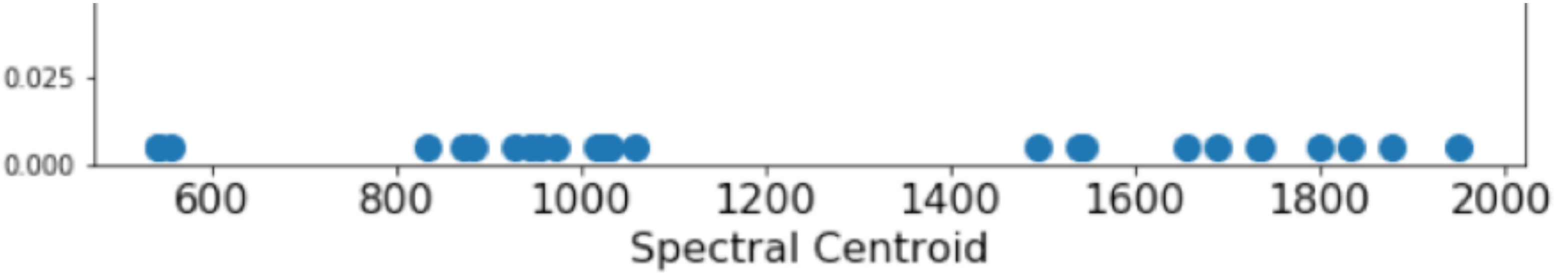


Automatic drum transcription-2

- Segmentation and feature extraction

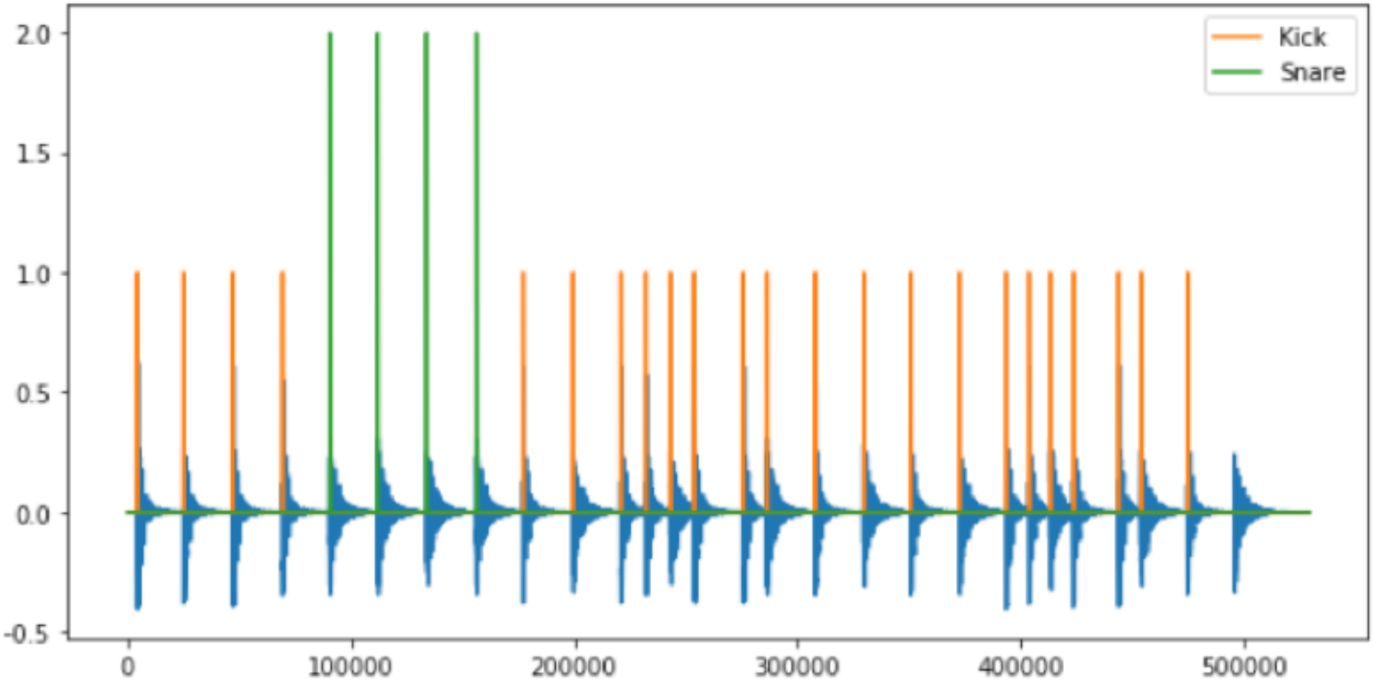


- The previous example



Automatic drum transcription-2

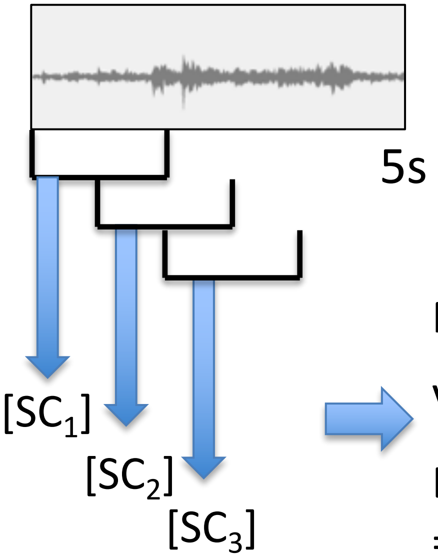
- More challenging example



You can find more feature extraction functions in the Librosa package

Feature summarization

- Using summary statistics over time to represent an audio expert as a single vector



$\vec{x}$ = <a_1, a_2, …, a_n>

Mean([SC_1, SC_2, SC_3, …, SC_t]) = a_1

Variance([SC_1, SC_2, SC_3, …, SC_t]) = a_2

Delta-mean([SC_1, SC_2, SC_3, …, SC_t])
= mean([$SC_2 - SC_1$, $SC_3 - SC_2$,…, $SC_t - SC_{t-1}$]) = a_3

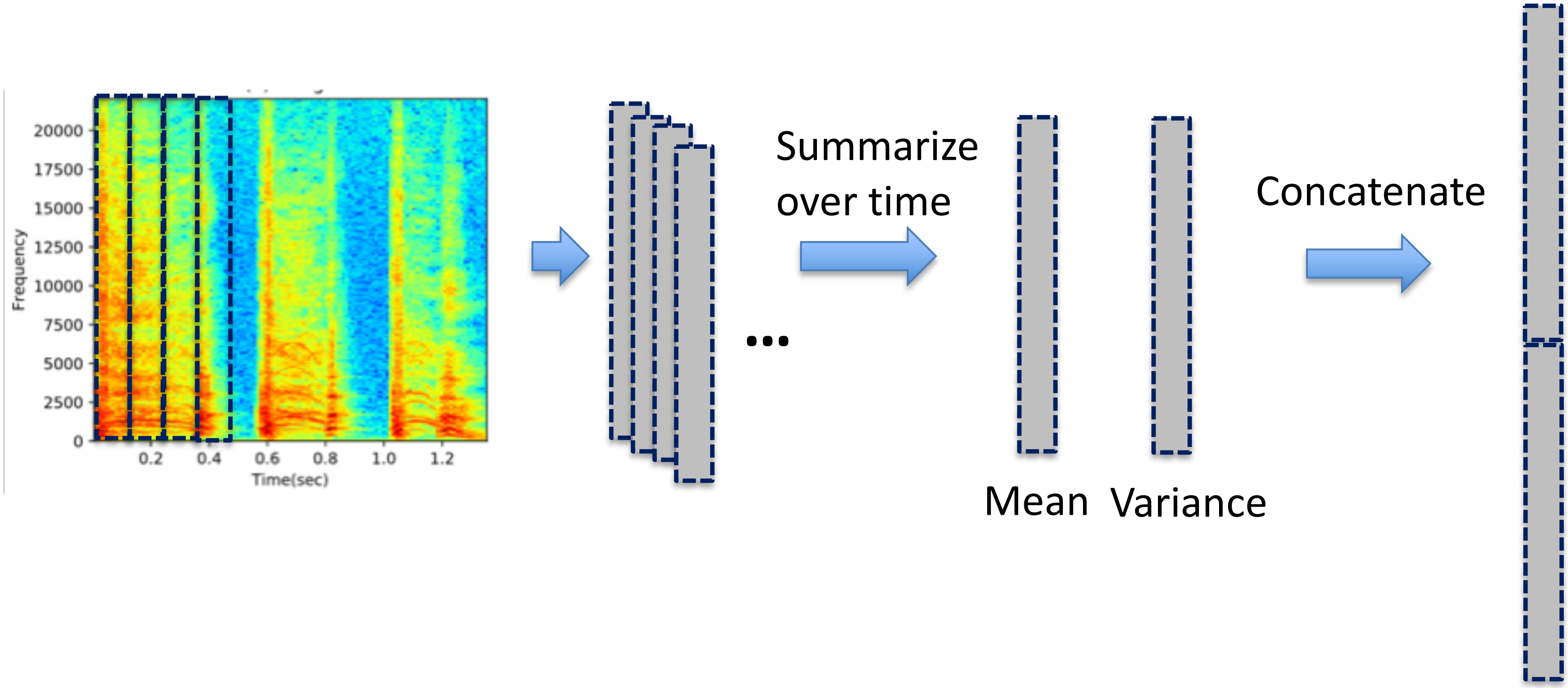
Delta-var([SC_1, SC_2, SC_3, …, SC_t])
= var([$SC_2 - SC_1$, $SC_3 - SC_2$,…, $SC_t - SC_{t-1}$]) = a_4

$\vec{x}$ = <a_1, a_2, a_3, a_4>

*SC: Spectral Centroid

Feature summarization

- Example for multi dimensional features



Example using a TINY spectrogram

Spectrogram

frequency

1	0	3	1	5
0	.4	0	.4	.2
0	29	1	20	10
10	10	10	10	10
0	0	0	50	0

Time

Mean
1
.2
12
10
10

Variance
3.2
0.03
124.4
0
400

Example using a TINY spectrogram

Spectrogram

frequency

1	0	3	1	5
0	.4	0	.4	.2
0	29	1	20	10
10	10	10	10	10
0	0	0	50	0

Time

Delta

-1	3	-2	4
.4	-.4	.4	-.2
29	-28	19	-10
0	0	0	0
0	0	50	-50

frame at (*t+1*) – frame at *t*

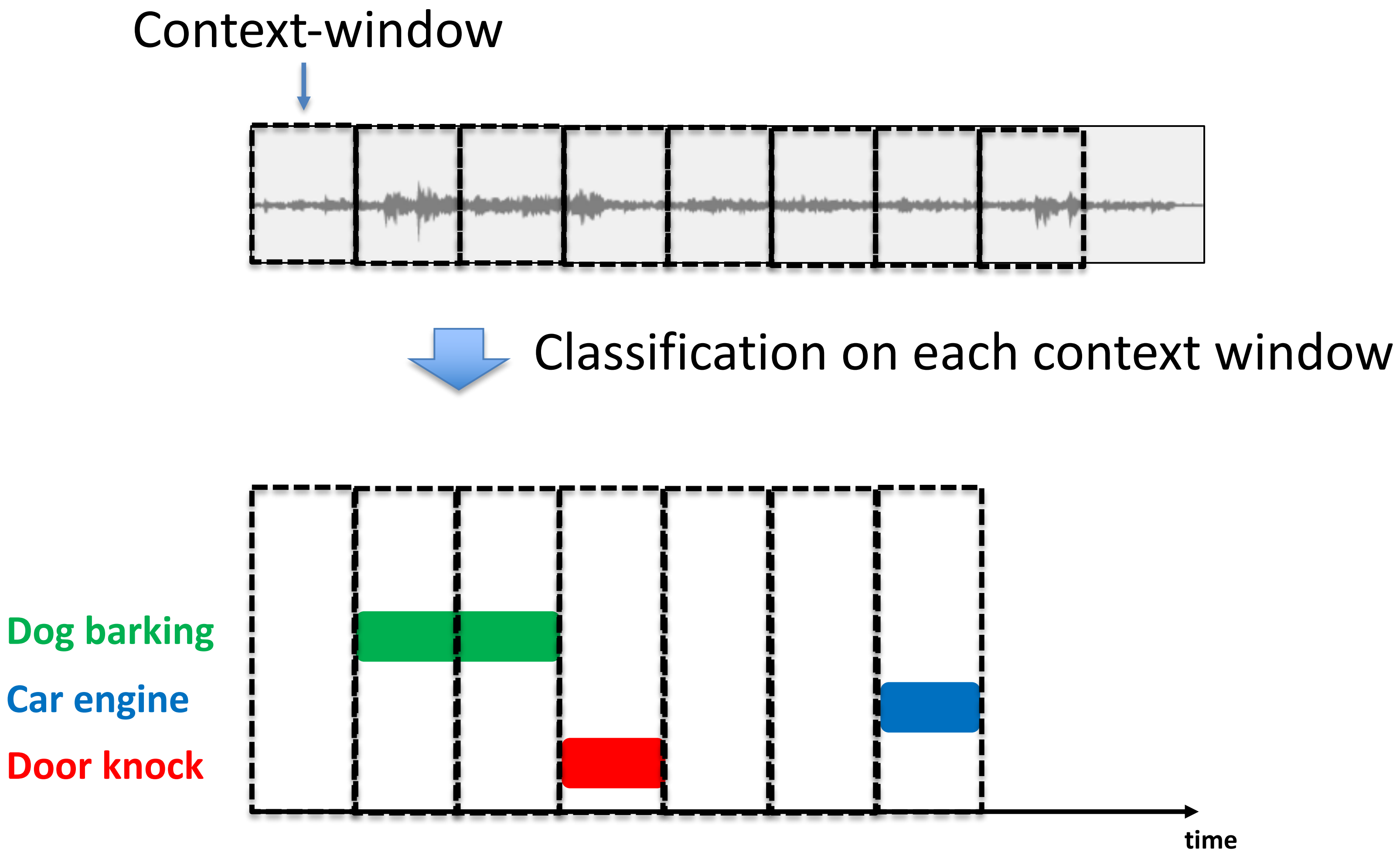
Delta -Mean	Delta -Variance
1	6.5
.05	.13
2.5	515.3
0	0
0	1250

Example using a TINY spectrogram

Mean	Variance	Delta -Mean	Delta -Variance
1	3.2	1	6.5
.2	0.03	.05	.13
12	124.4	2.5	515.3
10	0	0	0
10	400	0	1250

➔ The final feature vector (concatenating them all):
[1, .2, 12, 10, 10, 3.2, 0.03, 124.4, 0, 400, 1, .05, 2.5, 0, 0, 6.5, .13, 515.3, 0, 1250]

Sound Event Detection by Classification



Context-window

Classification on each context window

Dog barking

Car engine

Door knock

time

Challenges

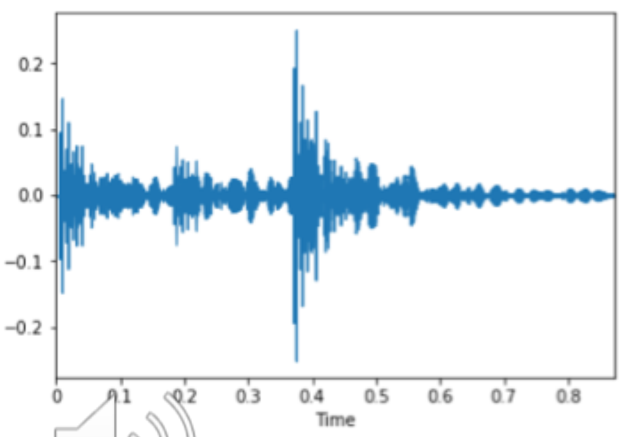
- Polyphonic environment, background noise
- Noisy labels
- Using a hierarchical relationship between audio labels
- Weakly labeled training dataset
- A small amount of **labeled** training dataset
- A large amount of **unlabeled** training dataset

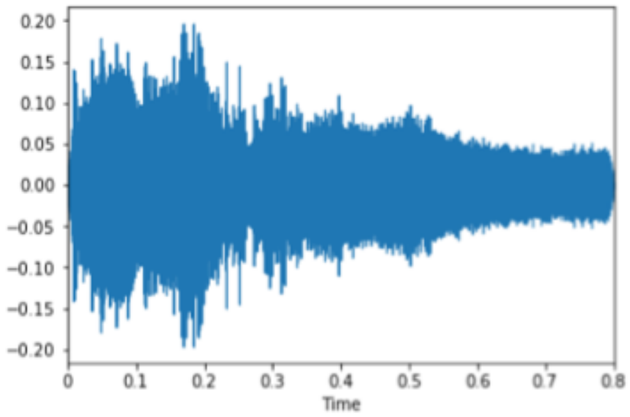
Datasets for sound object labeling

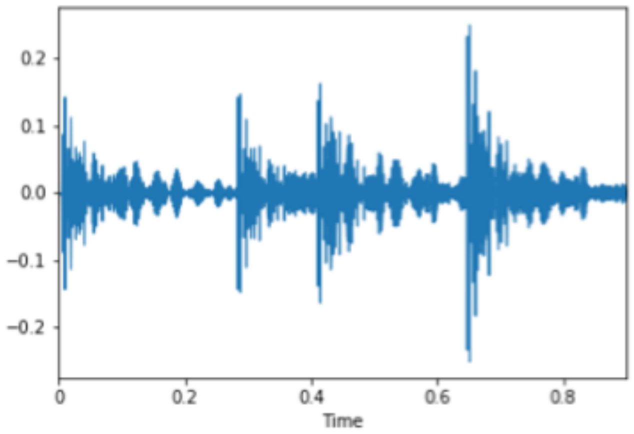
- Urban sound dataset: https://urbansounddataset.weebly.com/
- AudioSet: https://research.google.com/audioset/
- ESC: https://github.com/karoldvl/ESC-50
- DCASE: http://dcase.community/challenge2018/index
- IRMAS: https://www.upf.edu/web/mtg/irmas
- Vocal Imitation Set: https://zenodo.org/record/1340763#.XEtAJs9KiRs

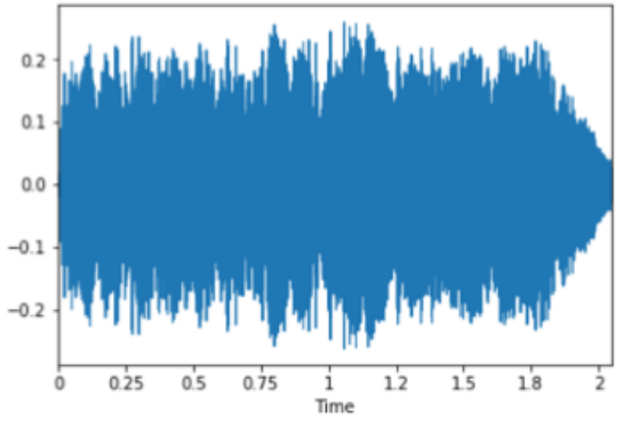
EXAMPLE: DOOR KNOCKING / PHONE RINGING CLASSIFICATION

Training data





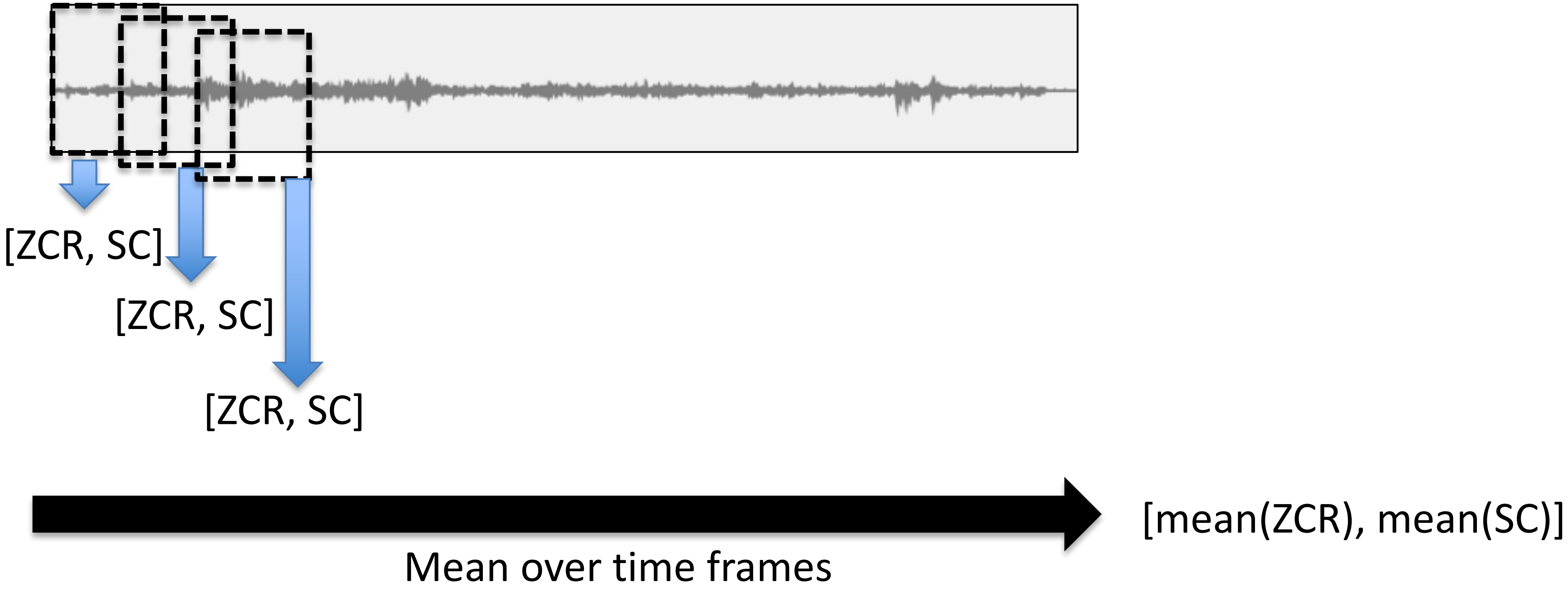




Feature extraction and summarization

- Zero-crossing rate and Spectral centroid
  - window length = 2048, hop length = 1024
  - Both features are represented as a single number for each time frame. So we get two feature values for each time frame (2-dimensional space)
  - The number of time frames vary with the length of each signal.
- To represent all the signals as the same size of feature vectors, we do summarization.
  - In this tutorial, I will take mean over frames.

Feature extraction and summarization



[ZCR, SC]

[ZCR, SC]

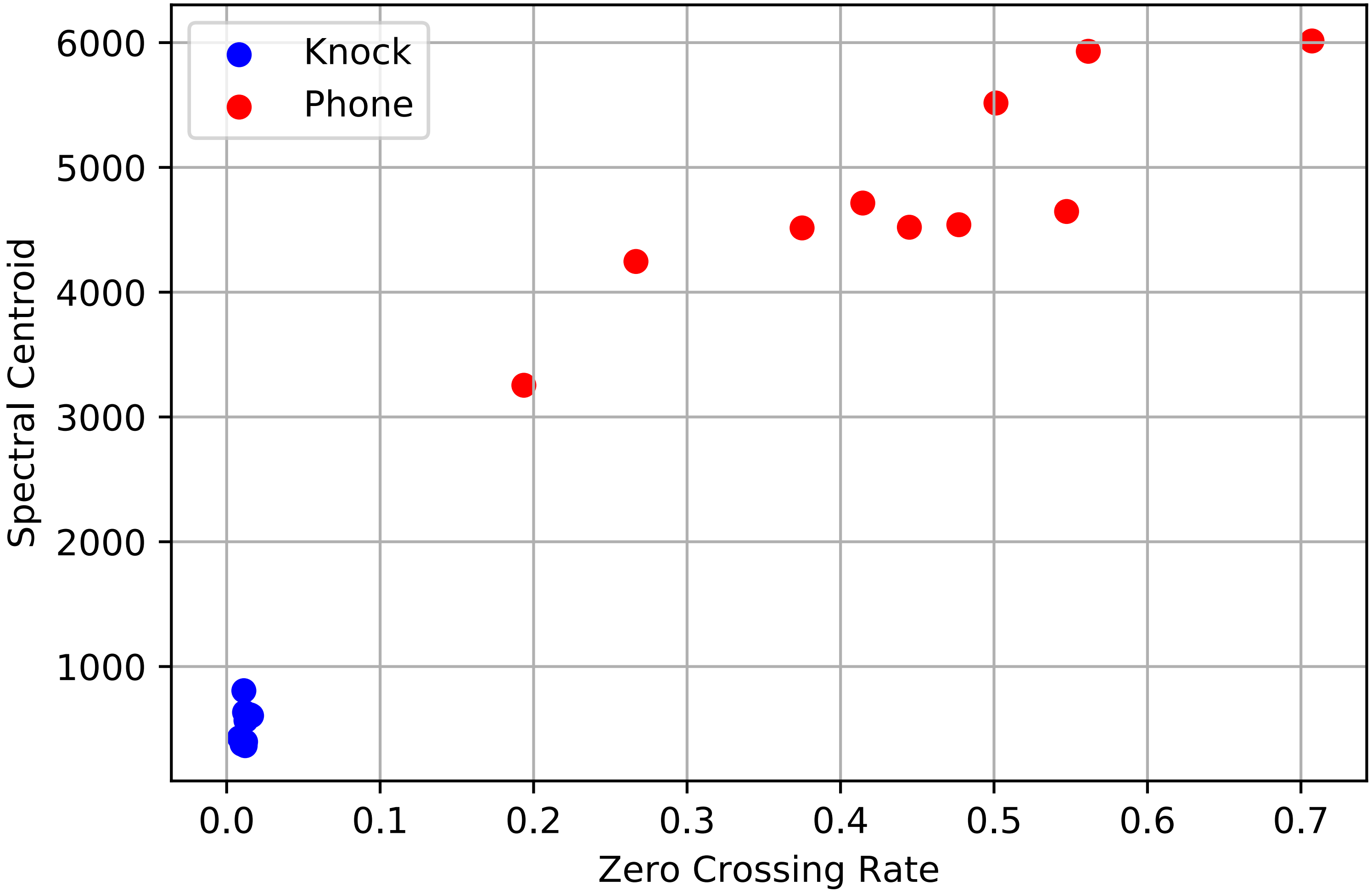
[ZCR, SC]

[mean(ZCR), mean(SC)]

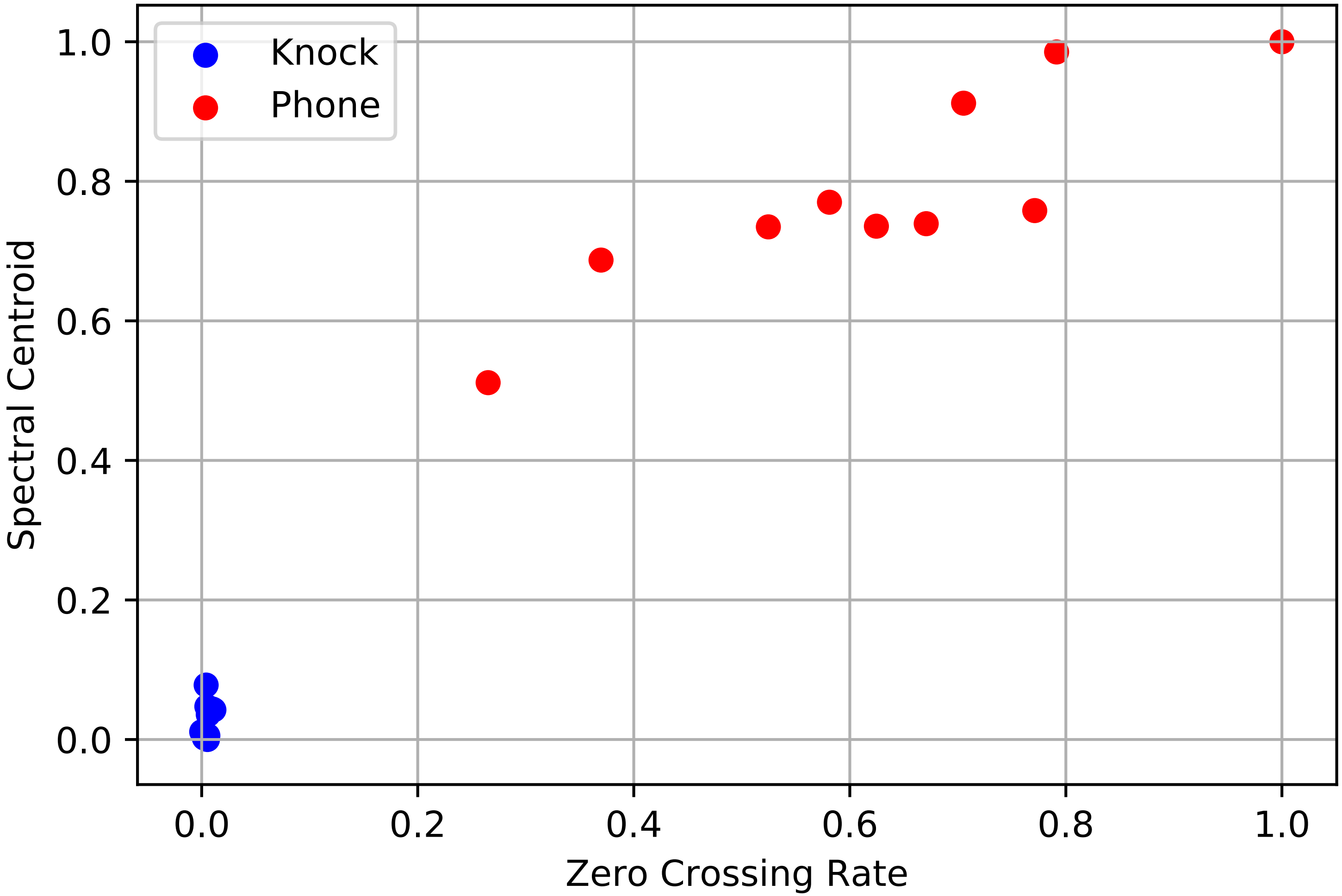
Mean over time frames

Now we can map all the signals into 2-dimensional feature space

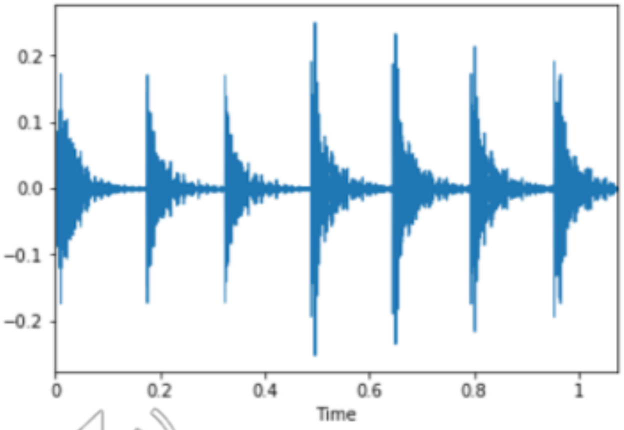
Plotting them in the feature space

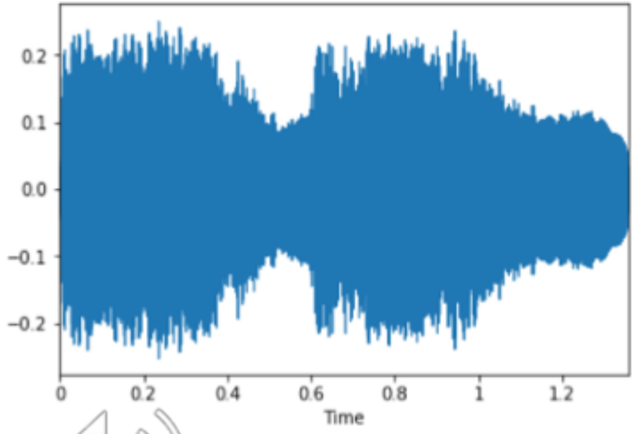


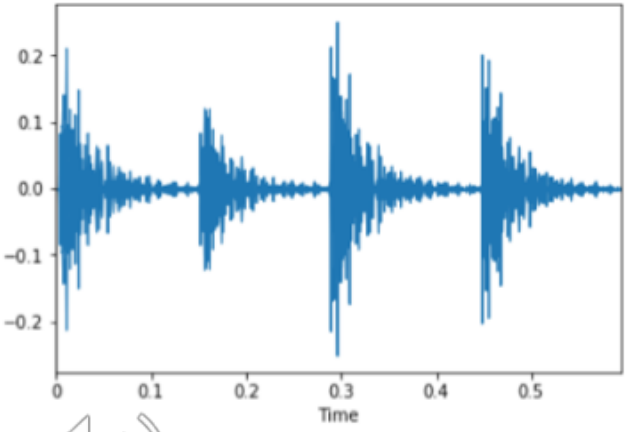
Feature scaling

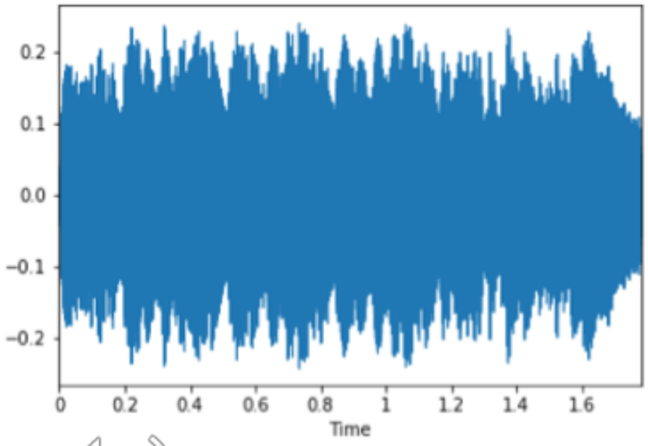


Testing examples



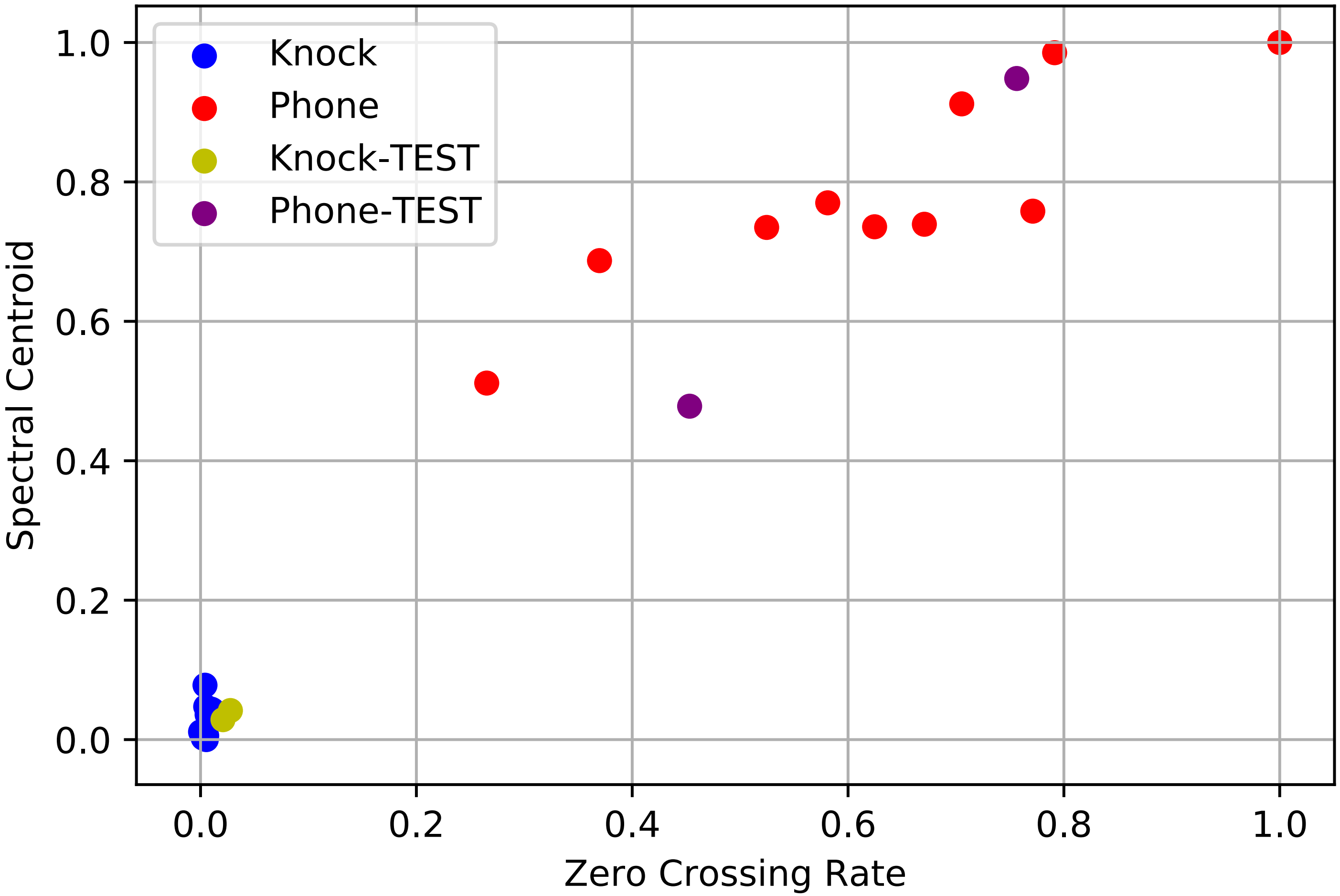






Plotting test examples

Nearest Neighbor classifier would perfectly work in this testing case


Knock
Phone
Knock-TEST
Phone-TEST
Spectral Centroid
Zero Crossing Rate