Feature Extraction & Engineering

8B

CS 3244 Machine Learning

NUS National University of Singapore | Computing

Recap from W08a

Student Learning Outcomes

What did we learn this week?

Data Issues

1. Linear Separability
2. Curse of Dimensionality
3. Imbalanced Data

Issue Template

1. **What** is the issue?
2. **Why** is it a problem?
3. **When** would it happen?
4. **How** to **check** for it?
5. **How** to **mitigate** it?

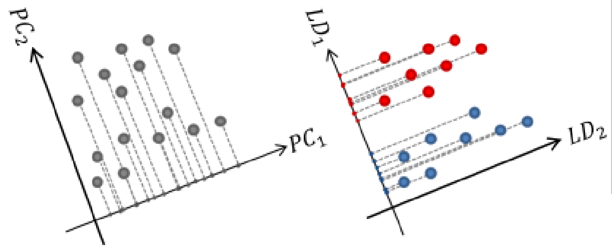
Mitigations

1. Linear PCA, LCA (for Linear Separability, Dimensionality Reduction)
2. Feature Selection (Recursive Feature Elimination, Correlation, Mutual Information)
3. Resampling (Undersampling, Oversampling, SMOTE)

PCA and LDA

PCA
Maximize Data Variance

LDA
Maximize Class Separation



Good for **dimensionality reduction** for supervised regression and unsupervised learning

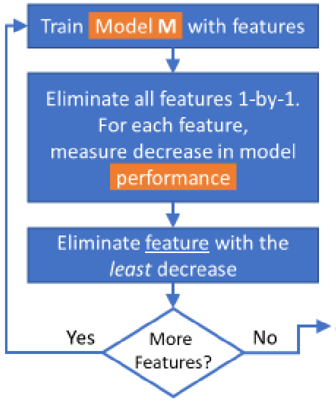
Good for **dimensionality reduction** for supervised classification

Steps

- All axes are orthogonal (independent)
1. **Identify** basis vectors
2. **Rank** basis vectors by importance
3. **Truncate** selection of basis vectors
   - Keeps more important features
   - Performs dimensionality reduction

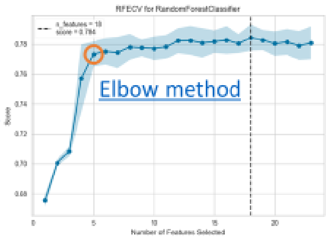
Issue: Curse of Dimensionality

5. **How** to **mitigate** it?
   - Feature Selection
     - **Wrapper methods** (e.g., RFE)
     - Filter methods

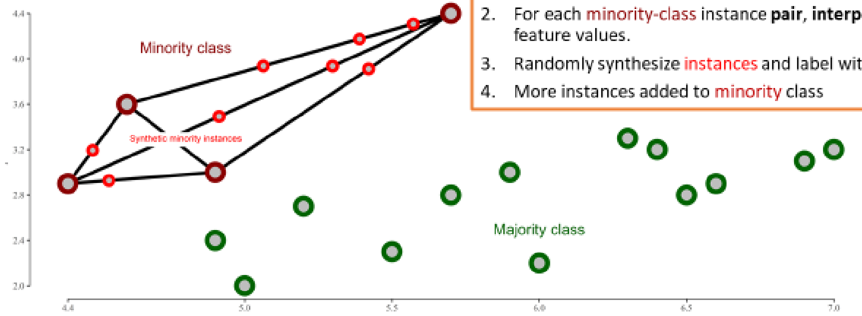


Recursive Feature Elimination (RFE)

Image Credit: https://www.scikit-yb.org/en/latest/api/model_selection/rfecv.html



Synthetic Minority Oversampling Technique (SMOTE)



Steps

1. Consider minority and majority instances in vector space.
2. For each minority-class instance **pair**, **interpolate** their feature values.
3. Randomly synthesize instances and label with minority class
4. More instances added to minority class

Image Credit: https://www.quora.com/Can-you-explain-me-SMOTE-Synthetic-Minority-Over-sampling-Technique-in-simple-terms

Issue: Linear Separability

5. **How** to **mitigate** it?

- Find useful features
  - Feature extraction (collect new features of your data)
- Transformation of features
  - Feature Engineering (e.g., $x \rightarrow x^2$)
  - Change Basis Vectors (e.g., PCA, LDA)
  - Kernel trick (e.g., for kernel SVM [W04b])
  - Feature Learning (e.g., Neural Networks [W09/10])

If data is not *linearly* separable, how can *linear* PCA and LDA make it *linearly* separable?

By reducing the number of non-linearly separable dimensions, this makes it easier/faster to find the optimal decision boundary, i.e., practical benefit.

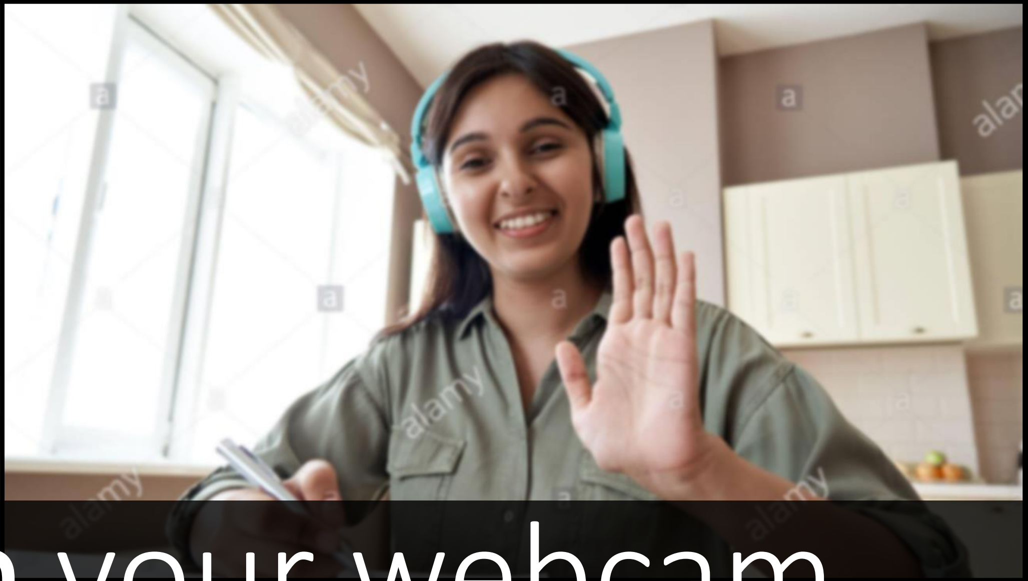
Week 08B: Learning Outcomes

1. Describe **issues** when extracting features for various data types
2. Describe **techniques** of feature extraction/engineering for different data types
   - Tabular
   - Temporal (Time Series)
   - Image
   - Text

Week 08B: Lecture Outline

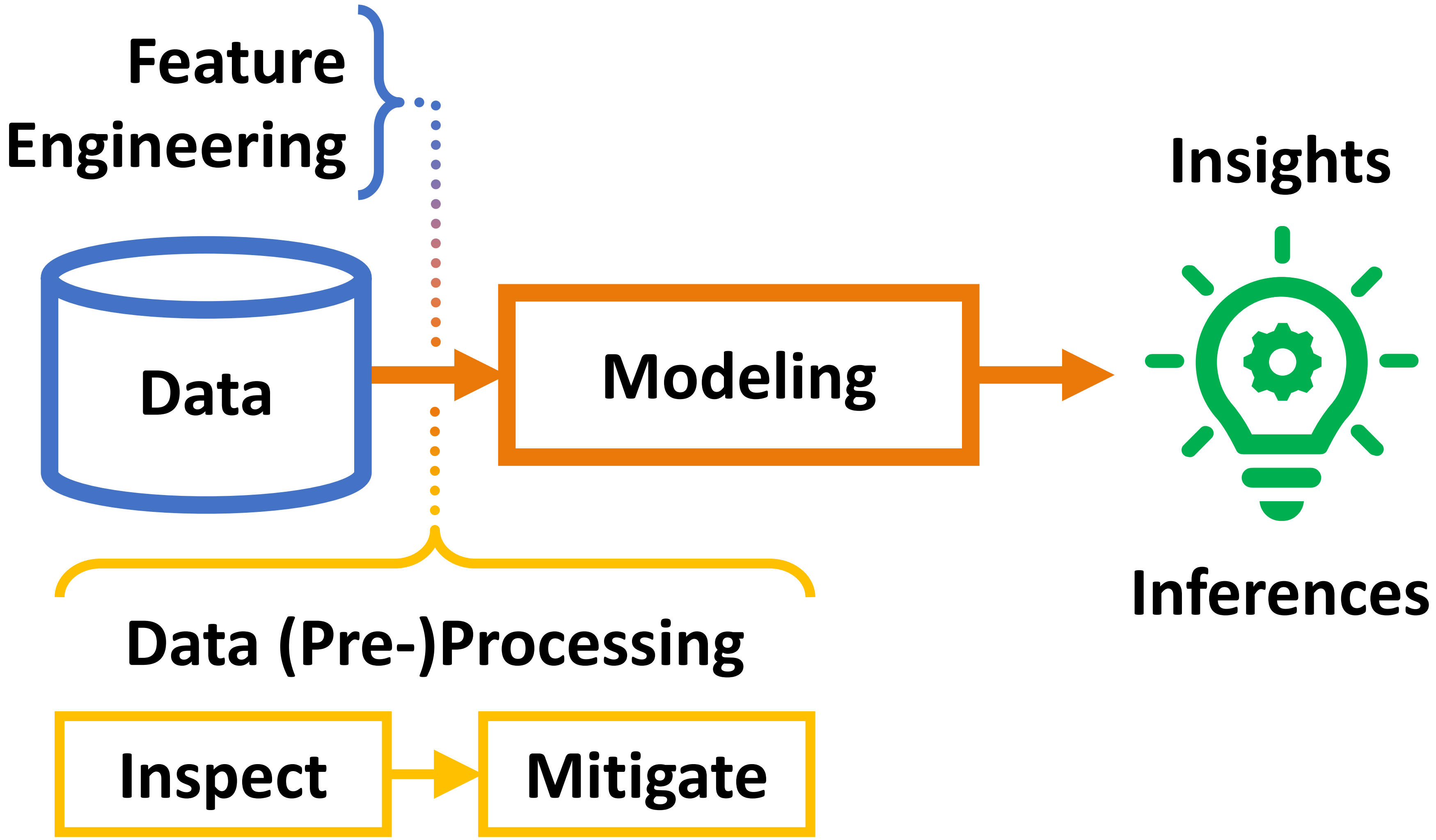
1. Overview: Feature Extraction and Engineering
2. Data Features
    1. Tabular Features
    2. Temporal (Time Series) Features
    3. Image Features
    4. Text Features

Please **turn on** your webcam

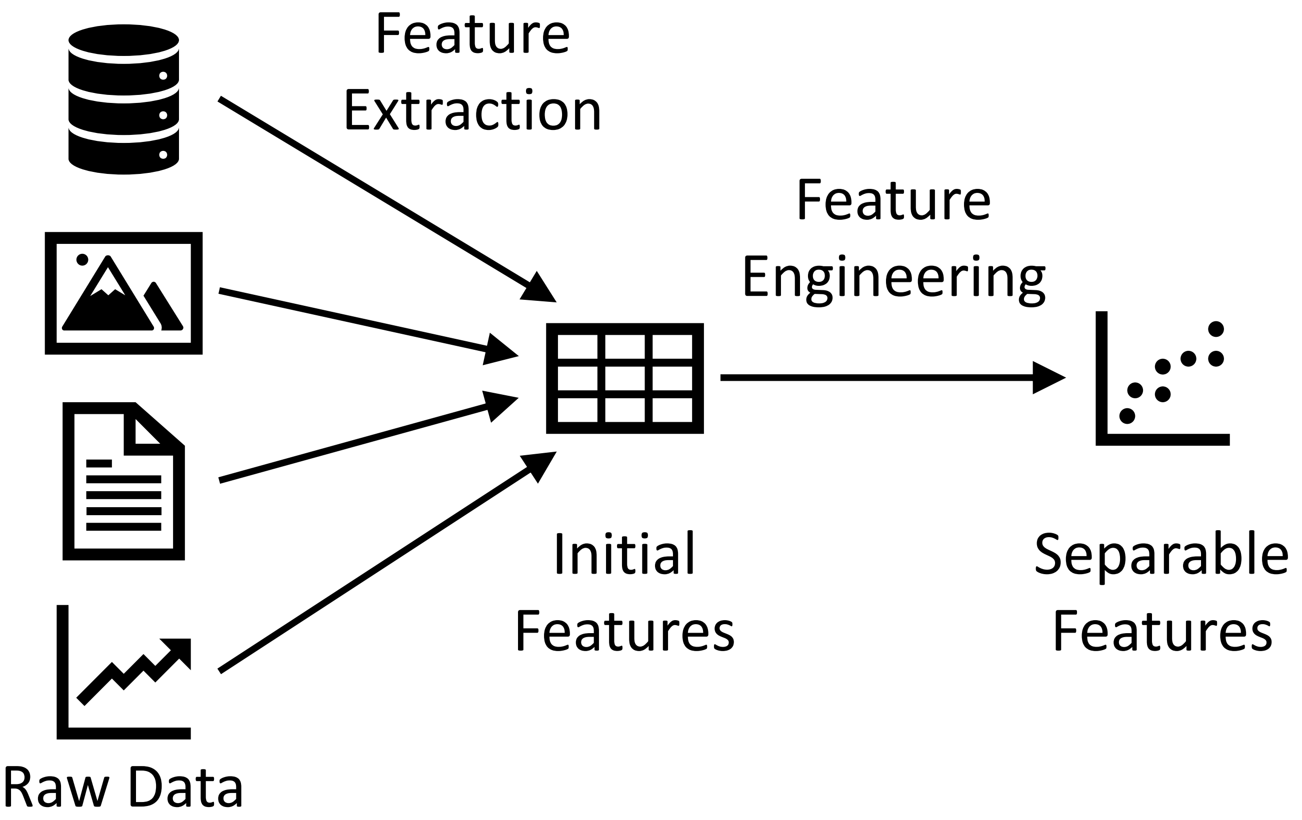


Mystery Student

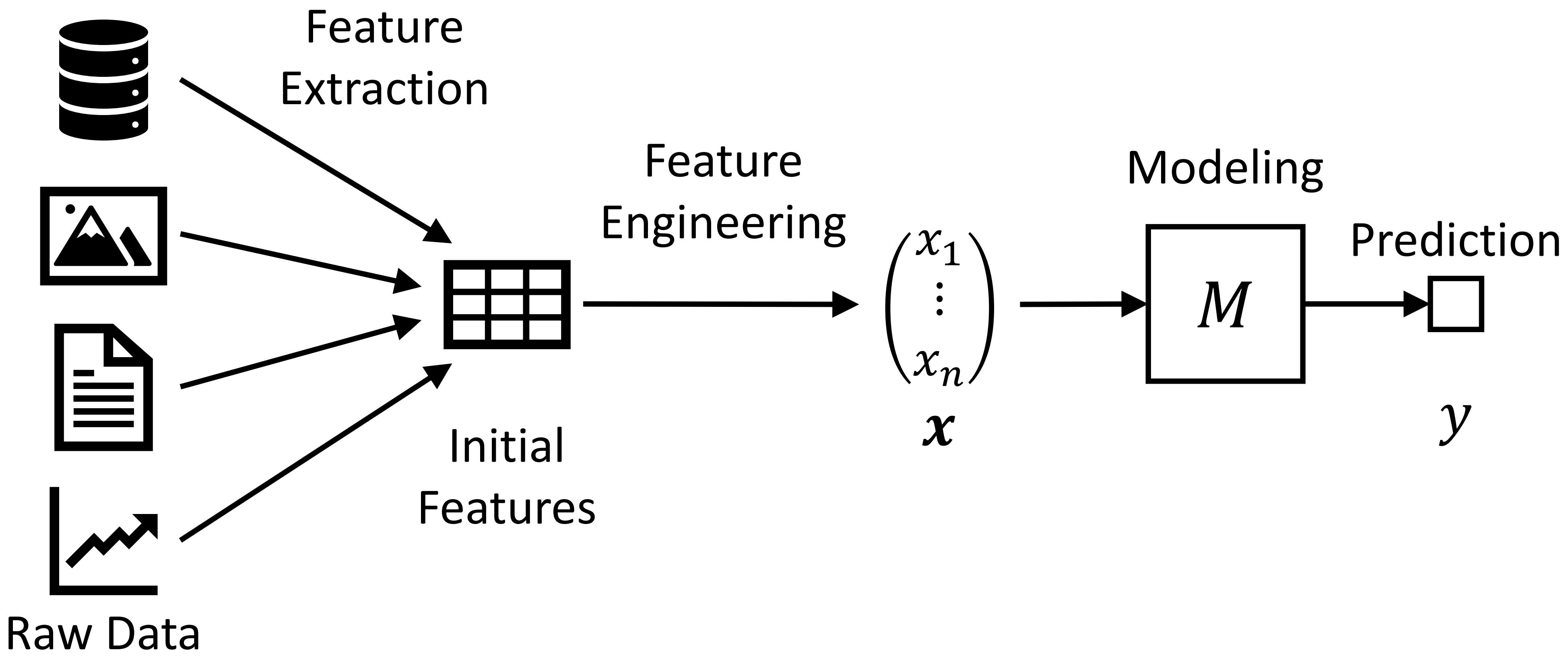
Machine Learning Pipeline



Feature Extraction and Engineering



Feature Extraction/Engineering → Modeling



Feature Extraction and Engineering

- Process of ***transforming* raw data** to improve the accuracy of models
- Enables you to
  - **Capture domain knowledge** (e.g., periodicity or relationships between features)
  - **Express non-linear relationships** using linear models
  - **Encode non-numeric features** to be used as inputs to models

Adapted from: [Joseph Gonzalez, John DeNero, Josh Hug]

Tabular Features

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Subscriptions → $$ Stopped Subscription = Churn

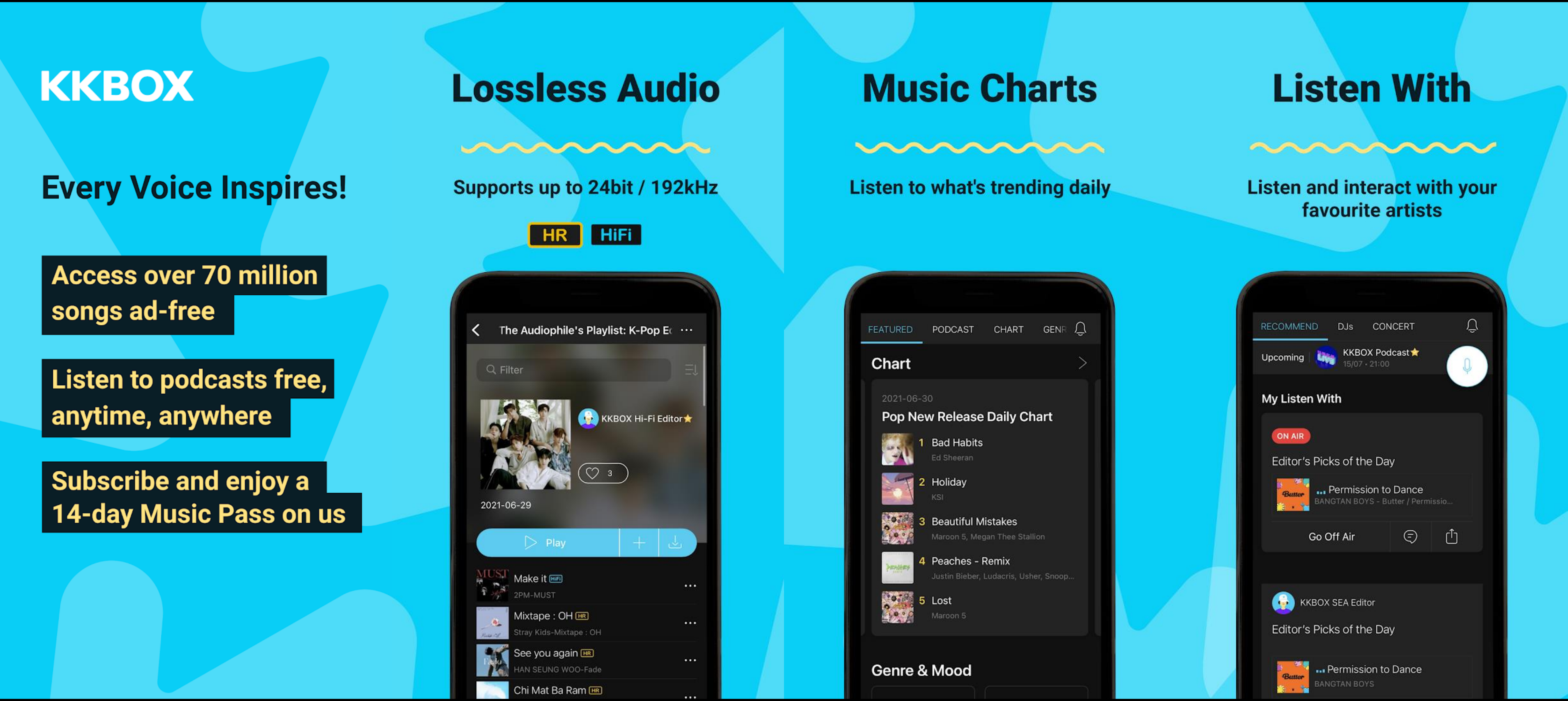


Image credit: https://play.google.com/store/apps/details?id=com.skysoft.kkbox.android&hl=en_NZ&gl=SG

Tabular Feature Extraction & Engineering

Prediction Task: **Customer Churn Prediction**

Database	Observations	# of Unique Users Covered	Dates	Data
members	6.7 mn KKBox users	6.7 mn users	Up to March 2017	• User's age • Gender • City • Initial registration date • Registration method (channel)
transactions	23 mn transactions	2.4 mn users (paying subscribers)	Jan. 2015 – March 2017	• Transaction date • Transaction amount • Subscription duration of that txn • Payment method • On auto renew (yes/no) • Cancelled subscriptions
user_logs	155 mn daily listening and user activity logs	2.5 mn users	Jan. 2015 – March 2017	• Date of activity • Total listening time that day (secs.) • # of unique songs started that day • % of song listened to: # of songs the user played for: 0-25% through, 25-50%, 50-75%, 75-98.5%, 98.5-100%
train	1 mn user churn results (yes/no)	1 mn users	Feb. 2017	• User's churn result for Feb. 2017 (yes/no)
test	1 mn user churn results (yes/no)	1 mn users	March 2017	• User's churn result for March 2017 (yes/no)

How to use?

- Data in multiple **separate tables**
- Need to **join** tables (e.g., with SQL, pandas)

How to use?

Labels

Source: https://medium.com/@chrishuskey/using-machine-learning-to-improve-subscriber-retention-at-kkbox-taiwans-spotify-before-a8c7702f8bd3

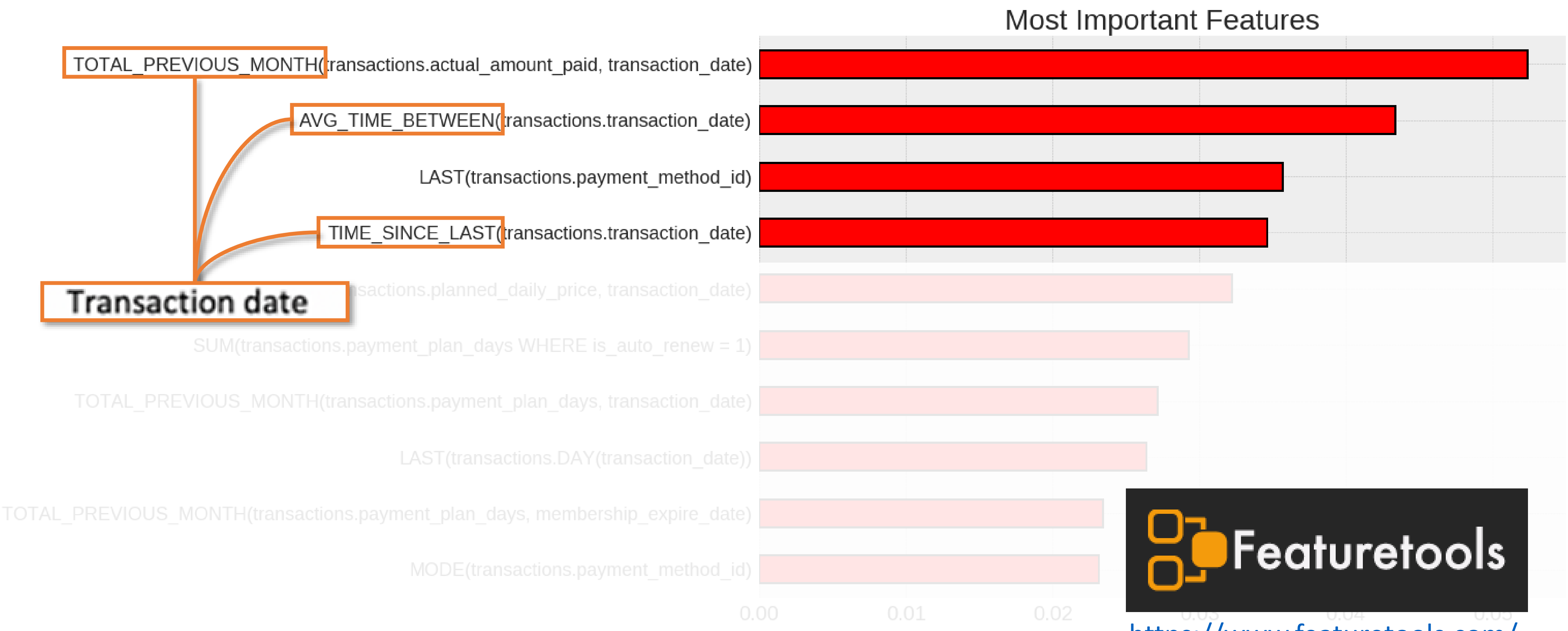
Tabular Feature Engineering:
Custom Equations based on Domain Knowledge

% of song listened to: # of songs the user played for: 0-25% through, 25-50%, 50-75%, 75-98.5%, 98.5-100%

$$\text{Song affinity score} = \frac{\text{\# of songs listened} \geq 98.5\% \text{ through (last 30 days)} - \text{\# of songs listened} \leq 50\% \text{ through (last 30 days)}}{\text{total \# of songs started (last 30 days)}}$$

Source: https://medium.com/@chrishuskey/using-machine-learning-to-improve-subscriber-retention-at-kkbox-taiwans-spotify-before-a8c7702f8bd3

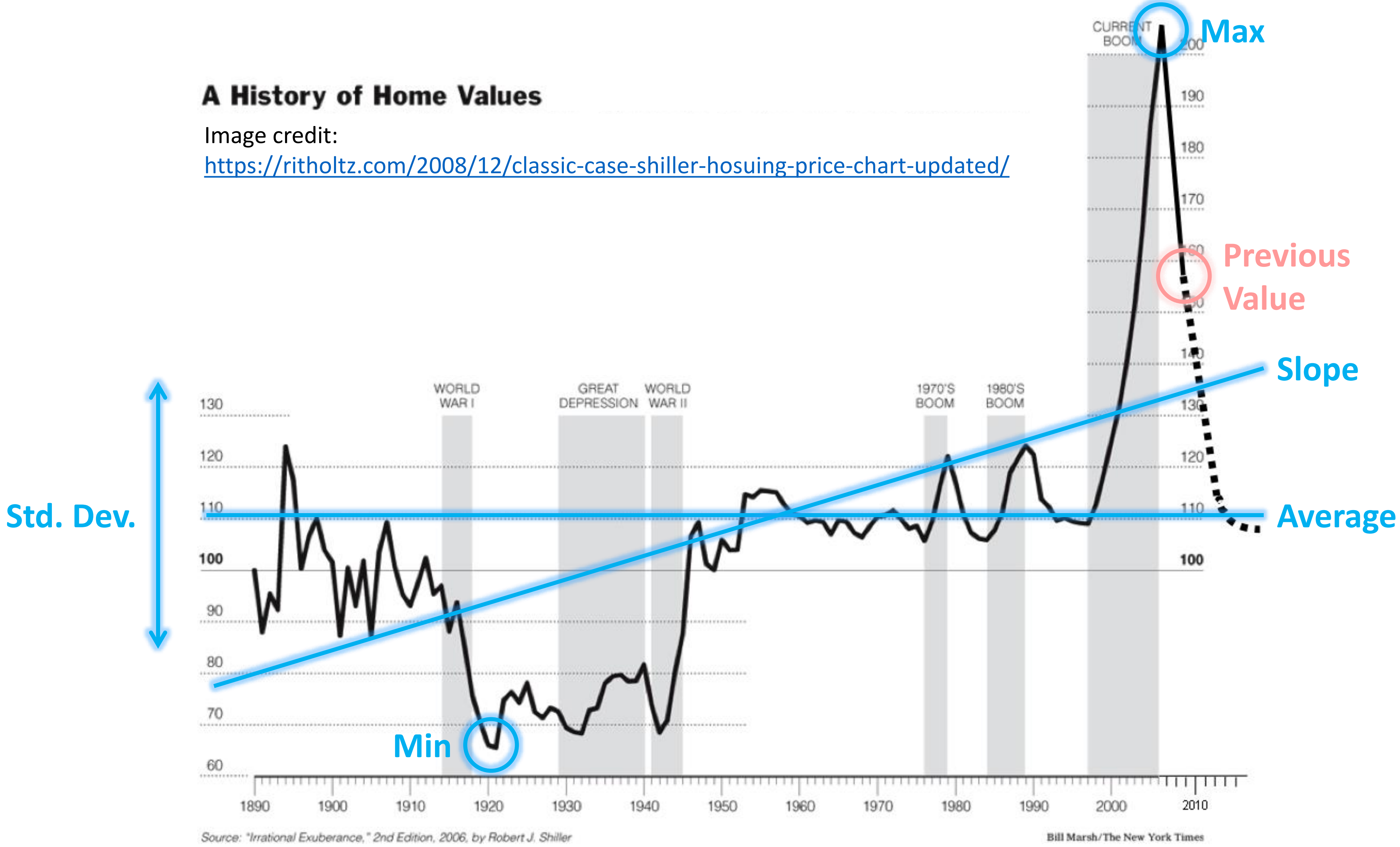
Tabular Feature Engineering:
Counting, Aggregation, Difference, Min, Max



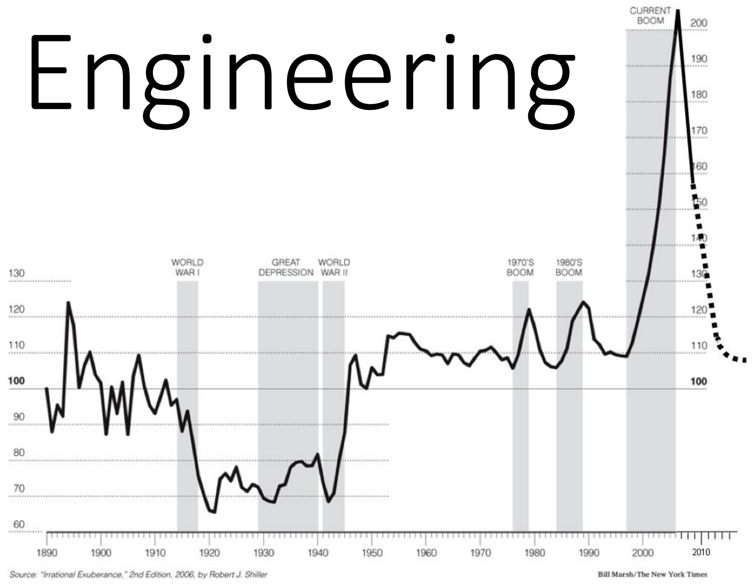
https://www.featuretools.com/

Source: https://github.com/Featuretools/predict-customer-churn

Temporal (Time) Features


A History of Home Values
Image credit:
https://ritholtz.com/2008/12/classic-case-shiller-hosuing-price-chart-updated/
Max
Previous Value
Slope
Average
Std. Dev.
Min
WORLD WAR I
GREAT DEPRESSION
WORLD WAR II
1970'S BOOM
1980'S BOOM
CURRENT BOOM
130
120
110
100
90
80
70
60
200
190
180
170
160
150
140
1890
1900
1910
1920
1930
1940
1950
1960
1970
1980
1990
2000
2010
Source: "Irrational Exuberance," 2nd Edition, 2006, by Robert J. Shiller
Bill Marsh/The New York Times

Temporal Feature Extraction & Engineering



- Prediction Task: **Home Price Prediction**
- Features
  - Previous value
  - Average
  - Variation: Standard Deviation
  - Range: Min, Max
  - Trend: Slope of linear fit

Aggregate Statistics (encode history)

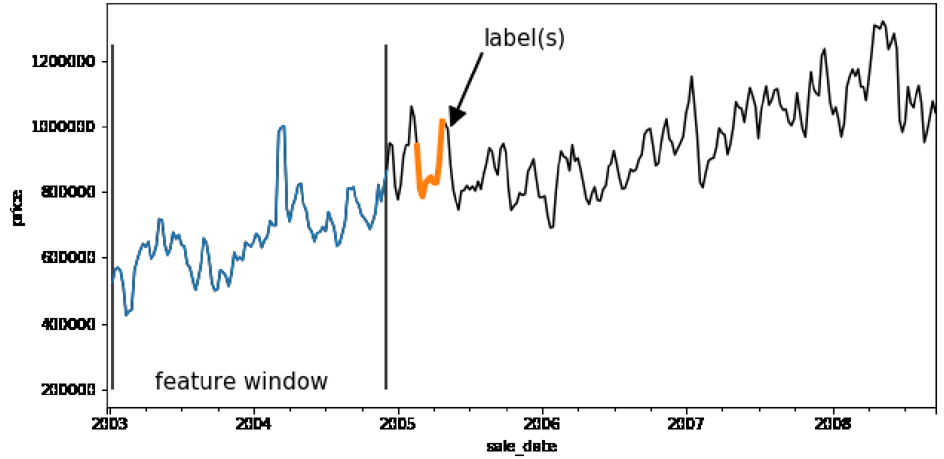
Linear regression

Total?

Small Time Window?

Sliding Time Window

- Prediction Task: **Price Prediction**
- Features
  - Moving Average
  - Moving Standard Deviation
  - Moving Range (Min, Max)
  - Moving Trend (Slope of linear fit)



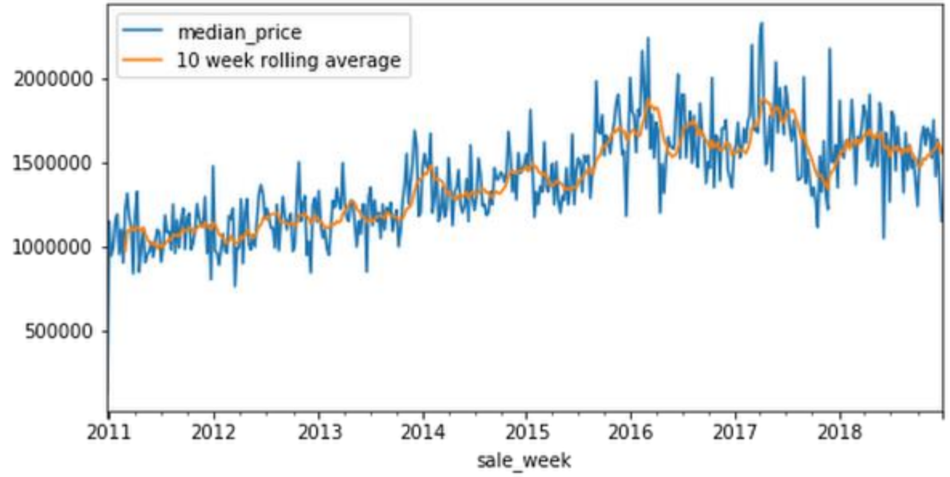


Image credit: https://cloud.google.com/blog/products/ai-machine-learning/how-to-quickly-solve-machine-learning-forecasting-problems-using-pandas-and-bigquery

Sound Classification

Temporal Feature Extraction & Engineering

- Prediction Task: **Sound Classification** (e.g., jackhammer, dog bark)
- Features
  - Previous value
  - Average
  - Variation: Standard Deviation
  - Range: Min, Max
  - Trend: Slope of linear fit
  - **Volume: Amplitude, Energy**
  - **Frequency: Periodicity, Spectrogram**

Aggregate Statistics (More history)

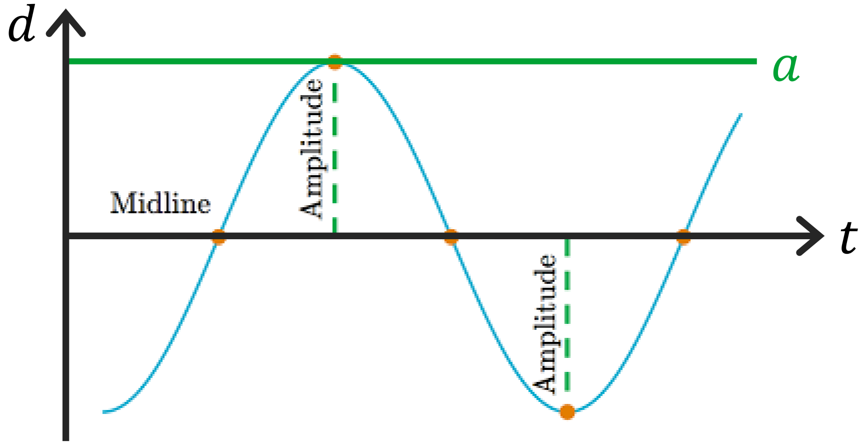
Linear regression

Wave analysis

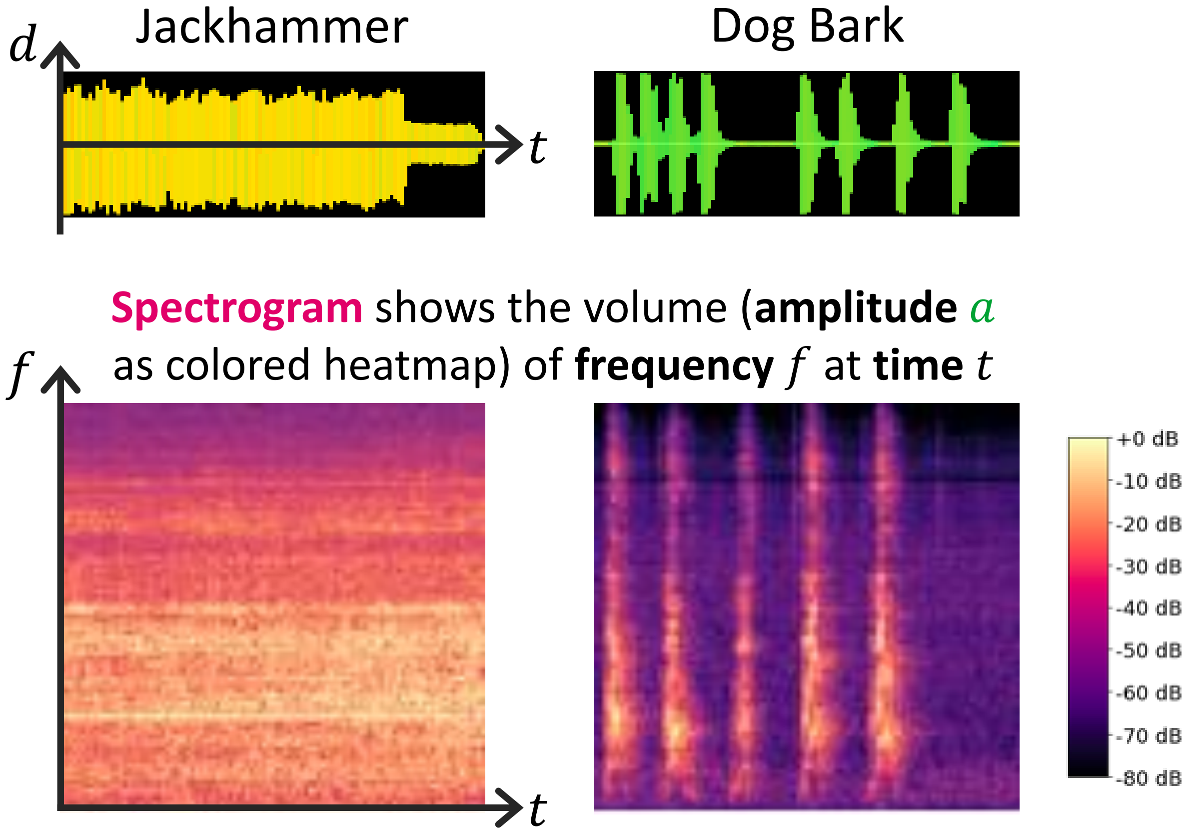
Audio Domain-Specific Features: Amplitude, Spectrogram

Not in exam

Amplitude a is maximum displacement d of wave



Displacement d over time t



Spectrogram shows the volume (**amplitude** a as colored heatmap) of **frequency** f at **time** t

Notice: spectrograms are **images**
Can extract image features!

Further reading: https://www.kdnuggets.com/2020/02/audio-data-analysis-deep-learning-python-part-1.html
Programming library: https://docs.scipy.org/doc/scipy/reference/generated/scipy.signal.spectrogram.html
Spectrogram source:
https://etown.medium.com/great-results-on-audio-classification-with-fastai-library-ccaf906c5f52

Questions!

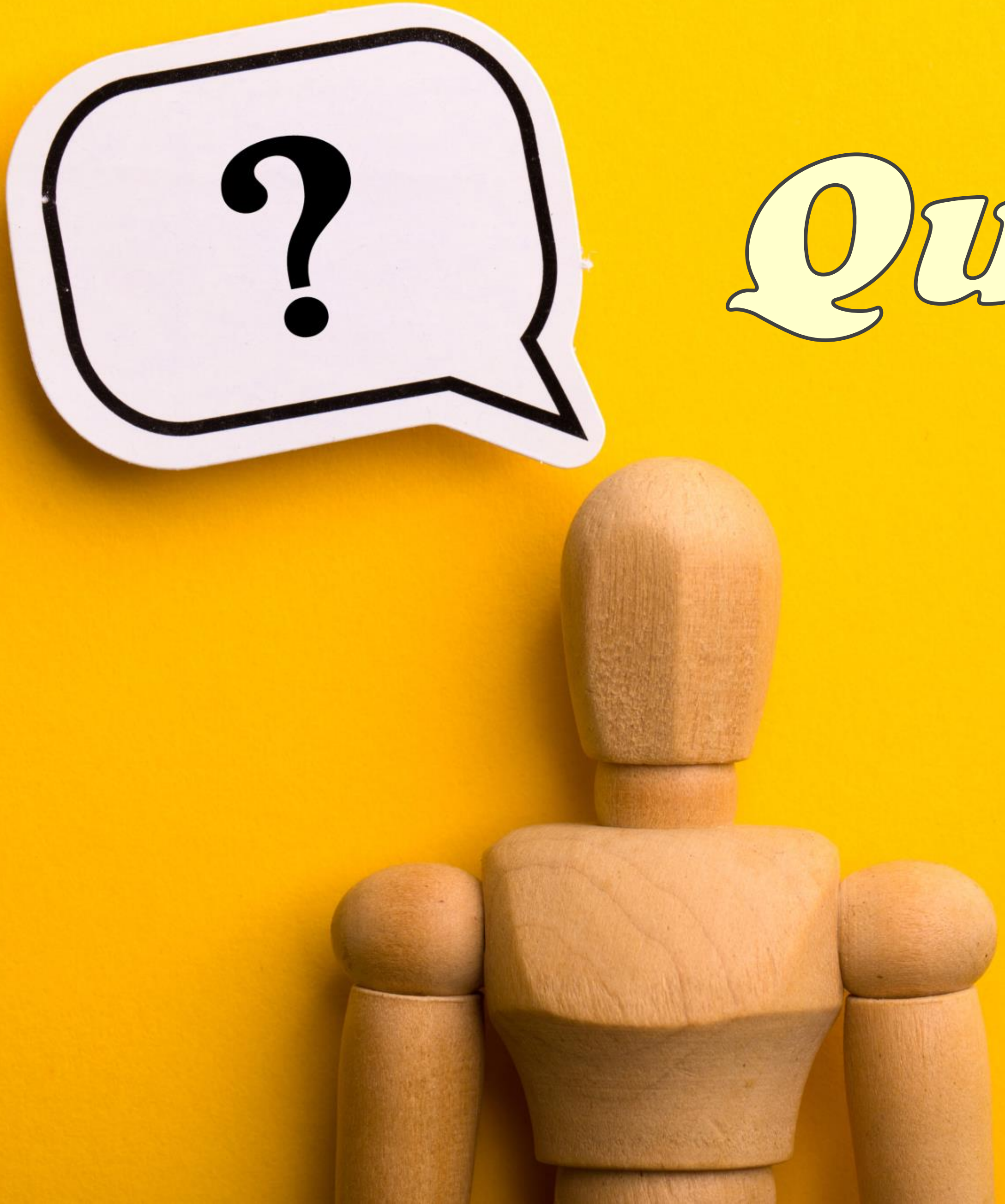


Image Features

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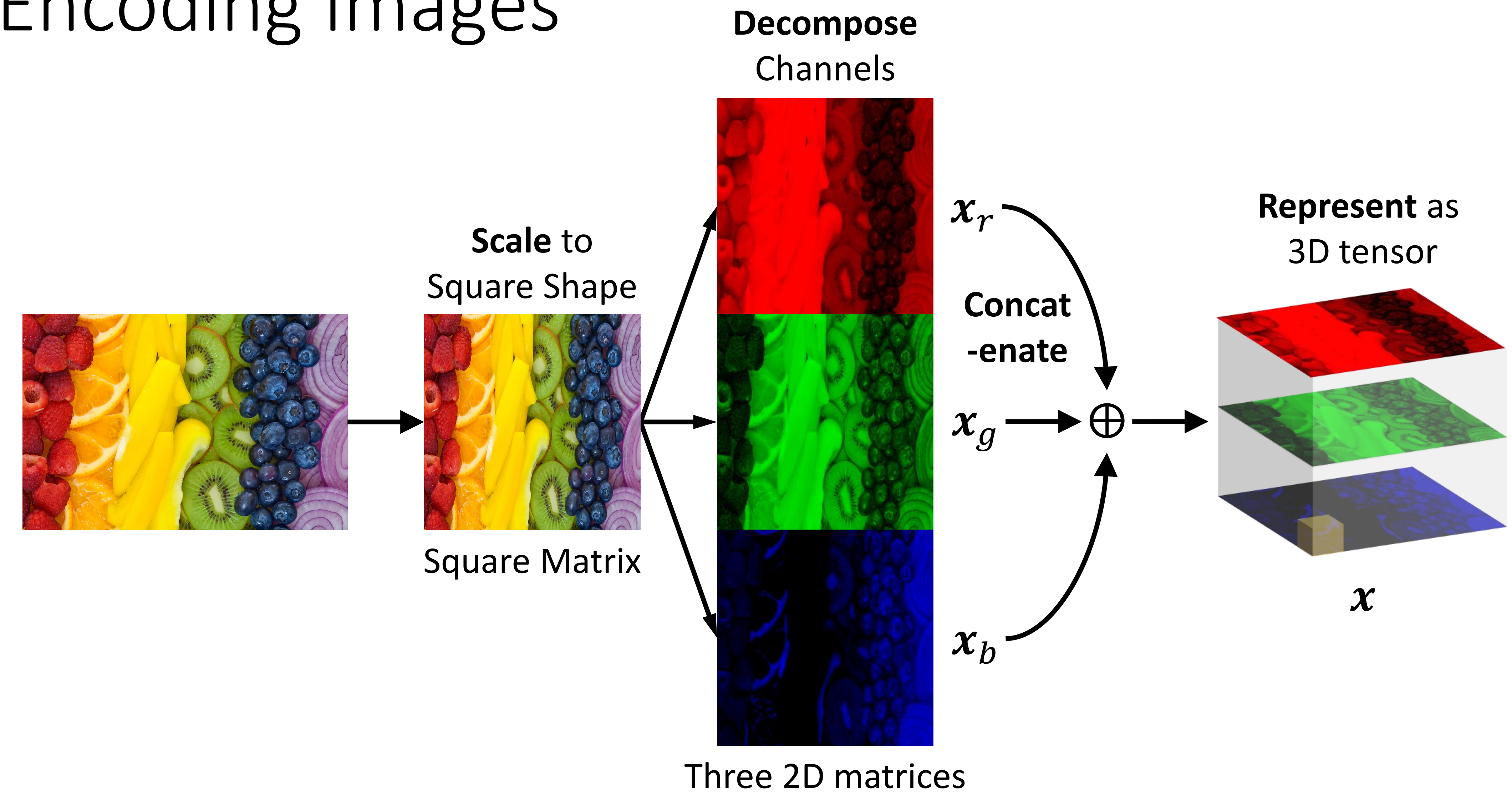
Encoding Images



What **features** would you use to...
Classify the <u>**sports ball**</u> in the image?

In Slack #general
1. <u>Respond</u> to thread (write) to suggest feature
2. <u>Emote</u> (👍 :+1:) to vote for feature

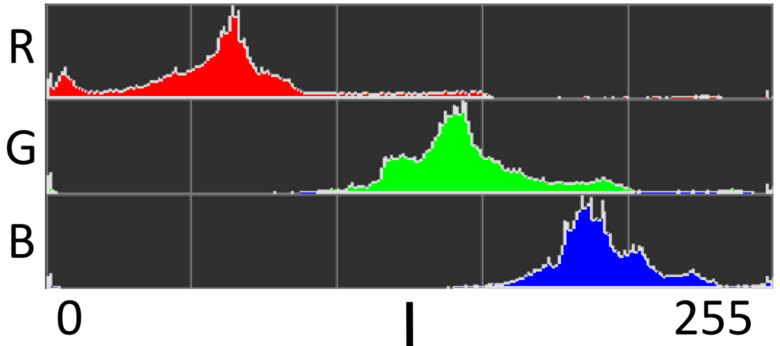
Basketball American Football Bowling Tennis Golf

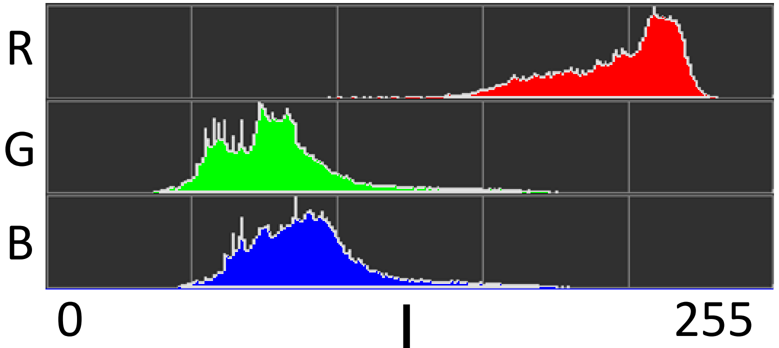
Image Feature Extraction & Engineering

- Prediction Task: **Sports ball classification**
- Features
  - Size? Photos may have different zoom levels
  - Color? Color Histogram → Vector
  - Shape? Edge detection → PCA
  - Texture?

Feature: Color Distribution (Histogram)

$$\boldsymbol{x} = \begin{pmatrix} n_{r0} & n_{g0} & n_{b0} \\ n_{r1} & n_{g1} & n_{b1} \\ \vdots & \vdots & \vdots \\ n_{r255} & n_{g255} & n_{b255} \end{pmatrix}$$






Basketball


American Football


Bowling


Tennis

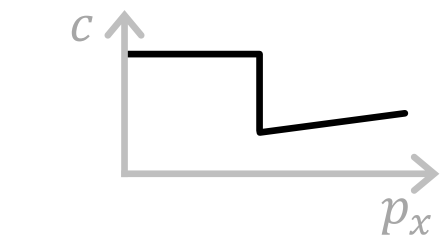

Golf

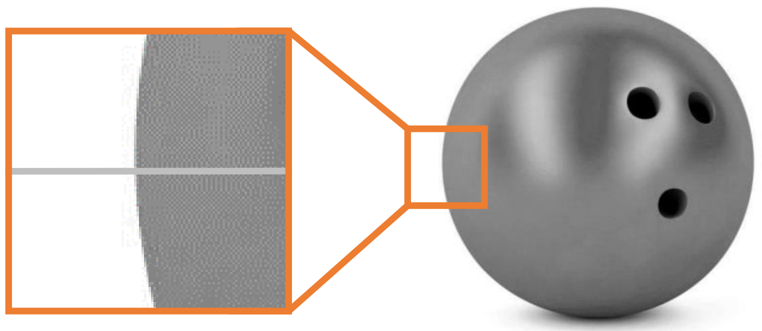
Feature: Color Distribution

Color may not be good, since balls can have the **same colors** even for different sports

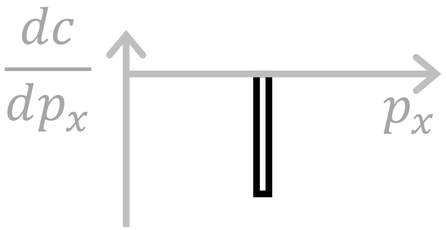
Basketball American Football Bowling Tennis Golf

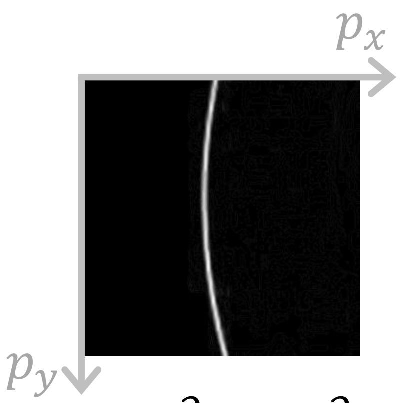
Feature: Edge Detection for Shape Features



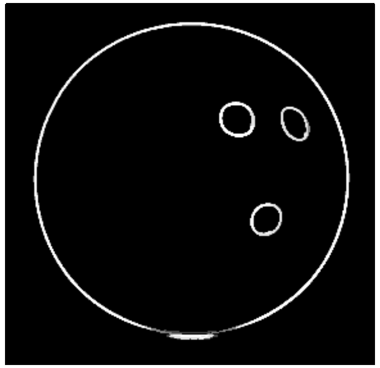


1. Convert to grayscale
2. Measure color c at each pixel position p_x





$$\nabla c = \frac{\partial c}{\partial p_x} + \frac{\partial c}{\partial p_y}$$



3. Compute 1st derivative $\frac{dc}{dp_x}$
   - High magnitude indicates edge
4. In 2D, calculate gradient ∇c
5. Threshold: $[\nabla c > c_{th}]$

Feature: Edge Detection Kernels

$$\frac{\partial c}{\partial p_x} \approx \frac{c_{(x+1,y)} - c_{(x-1,y)}}{p_{(x+1,y)} - p_{(x-1,y)}}$$

$$I_{p_x} = \begin{pmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix} \quad \boldsymbol{x} = \begin{pmatrix} c_{(-1,-1)} & c_{(0,-1)} & c_{(1,-1)} \\ c_{(-1,0)} & c_{(0,0)} & c_{(1,0)} \\ c_{(-1,1)} & c_{(0,1)} & c_{(1,1)} \end{pmatrix}$$

I_{p_x} is a Convolution Matrix (**Kernel**)

$*$ is **Convolution** operator
Means: element-wise multiply, then sum

$$\begin{aligned} I_{p_x} * \boldsymbol{x} = & \left(-c_{(-1,-1)} + 0 + c_{(1,-1)}\right) \\ & + \left(-c_{(-1,\ 0)} + 0 + c_{(1,\ 0)}\right) \\ & + \left(-c_{(-1,\ 1)} + 0 + c_{(1,\ 1)}\right) \end{aligned}$$

$$\boldsymbol{x} = \begin{pmatrix} 9 & 9 & 3 & 3 & 4 \\ 9 & 3 & 3 & 4 & 5 \\ 9 & 3 & 3 & 5 & 5 \\ 9 & 3 & 3 & 4 & 5 \\ 9 & 9 & 3 & 3 & 4 \end{pmatrix} \quad I_{p_x} * \boldsymbol{x} = \begin{pmatrix} -6-6-6 & -6+1+2 & 1+2+2 \\ -6-6-6 & 1+2+1 & 2+2+2 \\ -6-6-6 & 2+1-6 & 2+2+1 \end{pmatrix}$$

Feature: Edge Detection Kernels

$$\frac{\partial c}{\partial p_x} \approx \frac{c_{(x+1,y)} - c_{(x-1,y)}}{p_{(x+1,y)} - p_{(x-1,y)}}$$

$$I_{p_x} = \begin{pmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix} \qquad \boldsymbol{x} = \begin{pmatrix} c_{(-1,-1)} & c_{(0,-1)} & c_{(1,-1)} \\ c_{(-1,0)} & c_{(0,0)} & c_{(1,0)} \\ c_{(-1,1)} & c_{(0,1)} & c_{(1,1)} \end{pmatrix}$$

I_{p_x} is a Convolution Matrix (**Kernel**)

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Matrix convolutions can do differentiation in **parallel**
=> fast on GPU

$$\boldsymbol{x} = \begin{pmatrix} 9 & 9 & 3 & 3 & 4 \\ 9 & 3 & & 4 & 5 \\ 9 & & & & 5 \\ 9 & 3 & & 4 & 5 \\ 9 & 9 & 3 & 3 & 4 \end{pmatrix}$$

$$I_{p_x} * \boldsymbol{x} = \begin{pmatrix} -6-6-6 & -6+1+2 & 1+2+2 \\ -6-6-6 & 1+2+1 & 2+2+2 \\ -6-6-6 & 2+1-6 & 2+2+1 \end{pmatrix}$$

$$= \begin{pmatrix} -18 & -3 & 5 \\ -18 & 4 & 6 \\ -18 & -3 & 5 \end{pmatrix} \rightarrow \begin{pmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

Convolutional Neural Network (CNN) use kernels too! *More in W10*

Feature: Edge Detection Kernels (2D)

$$\frac{\partial c}{\partial p_x} \approx \frac{c_{(x+1,y)} - c_{(x-1,y)}}{p_{(x+1,y)} - p_{(x-1,y)}}$$

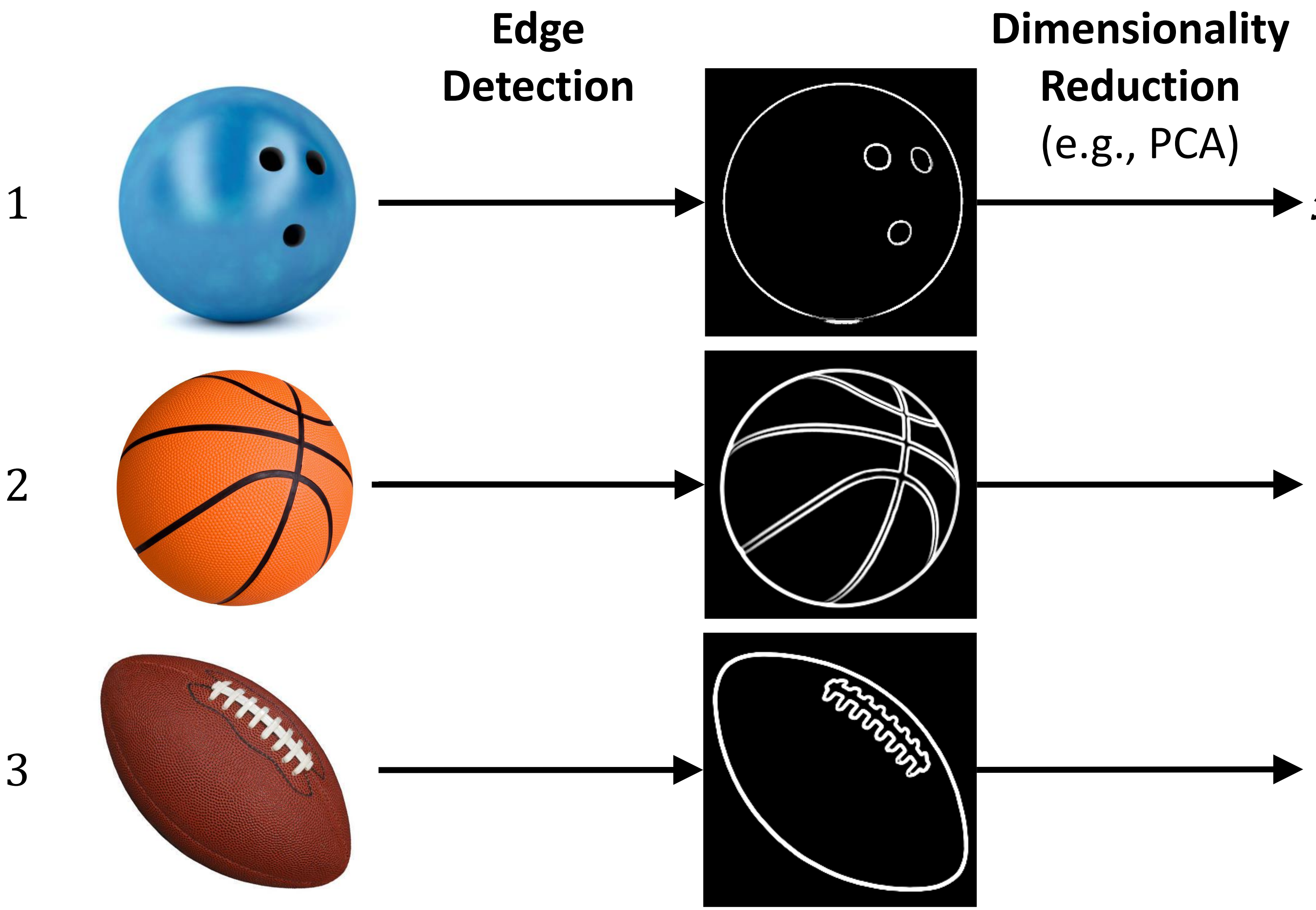
$$\frac{\partial c}{\partial p_y} \approx \frac{c_{(x,y+1)} - c_{(x,y-1)}}{p_{(x,y+1)} - p_{(x,y-1)}}$$

$$I_{p_x} = \begin{pmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{pmatrix}$$

$$I_{p_y} = \begin{pmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{pmatrix}$$

$$\nabla c = \frac{\partial c}{\partial p_x} + \frac{\partial c}{\partial p_y} \sim \left(I_{p_x} + I_{p_y}\right) * \boldsymbol{x}$$

Feature: Shape Feature Vector



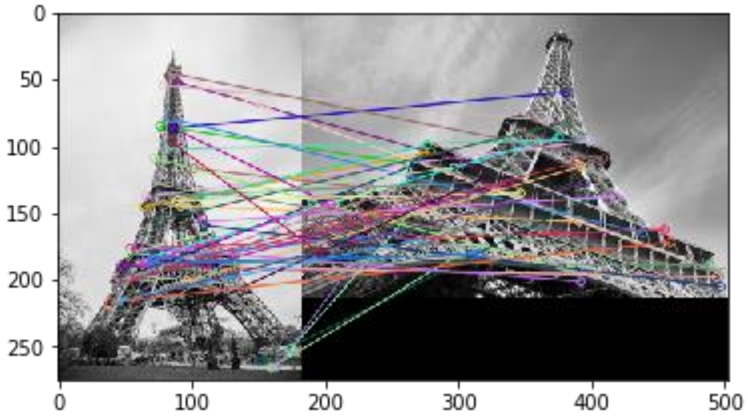
$$\boldsymbol{x}^{(1)} = \begin{pmatrix} PC_1^{(1)} \\ \vdots \\ PC_n^{(1)} \end{pmatrix}$$

$$\boldsymbol{x}^{(2)} = \begin{pmatrix} PC_1^{(2)} \\ \vdots \\ PC_n^{(2)} \end{pmatrix}$$

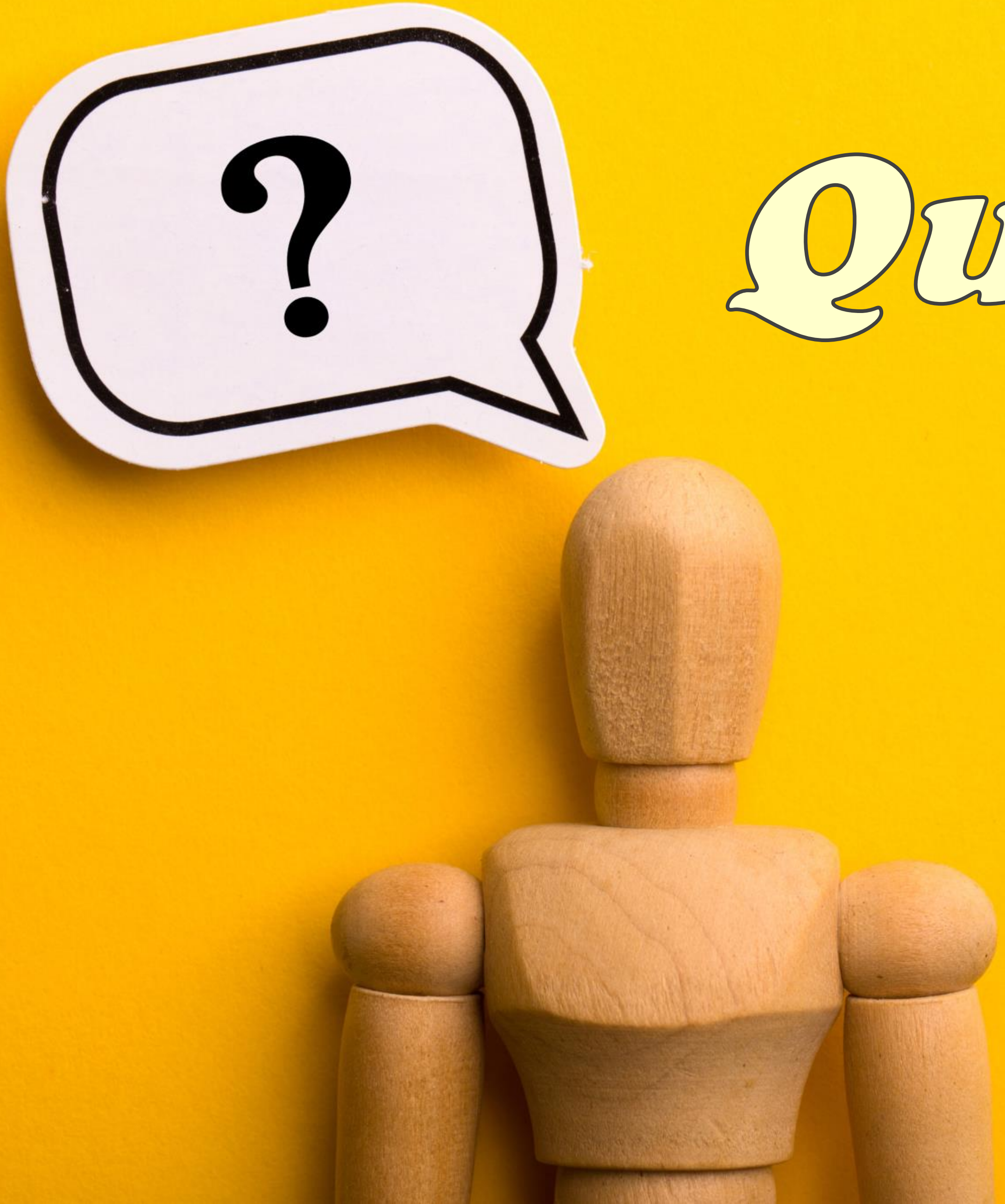
$$\boldsymbol{x}^{(3)} = \begin{pmatrix} PC_1^{(3)} \\ \vdots \\ PC_n^{(3)} \end{pmatrix}$$

Advanced methods

- Scale-invariant feature transform (SIFT) – Not in exam
  - Find **keypoints** in image to match in other images



  - Image → SIFT feature vector → Classify (e.g., kNN, logistic regression)
- Deep Learning (CNN) [W10]



Questions!

Text Features

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What **features** would you use to…
Classify the **sentiment** of the restaurant review?

"Chicken wings were amazing honestly" ★★★ **Positive**

"Amazing wings, but waaaay to long to wait." ★★☆ **Neutral**

"Not worth it! Too salty chicken and expensive!" ★☆☆ **Negative**

yelp Dataset

In Slack #general

1. Respond to thread (write) to suggest feature
2. Emote (👍 :+1:) to vote for feature

Text Feature Extraction & Engineering

- Prediction Task: **Review Sentiment Classification**
- Features
  - Text (String) Length?
  - Keywords? Which keywords?
  - Non-keywords? Stop words

Text Feature Extraction & Engineering

Problem / Objective	**Approach**
Extract words	Tokenization
Word variations	Stemming, Lemmatization
Uninformative words	Stop Word filtering
Identify informative words	Bag-of-Words (BOW)

Tokenization

- Split a single `string` of text into an `array` of substrings
- Split with **delimiters** (e.g., whitespaces ‘ ’, newline ‘\n’, punctuations ‘,.?’)

Original Text	Tokenized into Array of Words
“Chicken wings were amazing honestly”	[‘chicken’, ‘wings’, ‘were’, ‘amazing’, ‘honestly’]
“Amazing wings, but waaaay to long to wait.”	[‘amazing’, ‘wings’, ‘but’, ‘waaaay’, ‘to’, ‘long’, ‘to’, ‘wait’]
“Not worth it! Too salty chicken and expensive!”	[‘not’, ‘worth’, ‘it’, ‘too’, ‘salty’, ‘chicken’, ‘and’, ‘expensive’]

Stemming and Lemmatization

Stemming	Lemmatization
Truncates words *without* contextual knowledge.	Groups *inflected* forms of a word as identified in a dictionary.
Base form of word is called ***stem***	Base form of word is called ***lemma***
Remove word endings: 'ed', 'ing', 'ly', 'ment', etc.	Looks up dictionary (e.g., WordNet) to find lemma, and replace word with lemma
Easier to implement	Harder to implement
Runs faster	Runs slower
E.g.: walking, walked → walk better → better having → hav	E.g.: walking, walked → walk better → good having → have

Further reading: https://towardsdatascience.com/stemming-vs-lemmatization-2daddabcb221
Programming library: https://www.nltk.org/api/nltk.stem.html

Stop Words

- Most **common** words for the language that have **little semantic meaning** (uninformative)
- Programming libraries maintain list of stop words (e.g., NLTK)
- Problems? May remove actually informative words (e.g., 'not')

127 NLTK Stop Words

['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', 'his', 'himself', 'she', 'her', 'hers', 'herself', 'it', 'its', 'itself', 'they', 'them', 'their', 'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this', 'that', 'these', 'those', 'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have', 'has', 'had', 'having', 'do', 'does', 'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or', 'because', 'as', 'until', 'while', 'of', 'at', 'by', 'for', 'with', 'about', 'against', 'between', 'into', 'through', 'during', 'before', 'after', 'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on', 'off', 'over', 'under', 'again', 'further', 'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how', 'all', 'any', 'both', 'each', 'few', 'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not', 'only', 'own', 'same', 'so', 'than', 'too', 'very', 's', 't', 'can', 'will', 'just', 'don', 'should', 'now']

Original Text	After Stop Word filtering
"Chicken wings were amazing honestly"	"Chicken wings ~~were~~ amazing honestly"
"Amazing wings, but waaaay to long to wait."	"Amazing wings, ~~but~~ waaaay ~~to~~ long ~~to~~ wait."
"Not worth it! Too salty chicken and expensive!"	"~~Not~~ worth it! ~~Too~~ salty chicken ~~and~~ expensive!"

Further reading: https://medium.com/@saitejaponugoti/stop-words-in-nlp-5b248dadad47

Bag of ~~Letters~~
Words

Image credit: https://cdn-o.fishpond.co.nz/0218/542/604/1116441768/original.jpeg

Bag-of-Words (BOW) Encoding

1. Preprocess string s to array of words $\boldsymbol{w}$
2. Array of words → One-hot vector (fixed length)
3. $\mathrm{BOW}(\boldsymbol{w}) \rightarrow \boldsymbol{x}$
4. Problem: high dimensions if many words

$$x^{(1)} = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \qquad x^{(2)} = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 0 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

$$\boldsymbol{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_{13} \end{pmatrix}$$

#	Original Text s	Pre-Processed Words $\boldsymbol{w}$	chicken	wings	amazing	honestly	but	way	too	long	wait	not	worth	salty	expensive
1	"Chicken wings were amazing honestly"	['chicken', 'wings', 'amazing', 'honestly']	1	1	1	1	0	0	0	0	0	0	0	0	0
2	"Amazing wings, but waaaay to long to wait."	['amazing', 'wings', 'but', 'way', 'too', 'long', 'wait']	0	1	1	0	1	1	1	1	1	0	0	0	0
3	"Not worth it! Too salty chicken and expensive!"	['not', 'worth', 'too', 'salty', 'chicken', 'expensive']	1	0	0	0	0	0	1	0	0	1	1	1	1

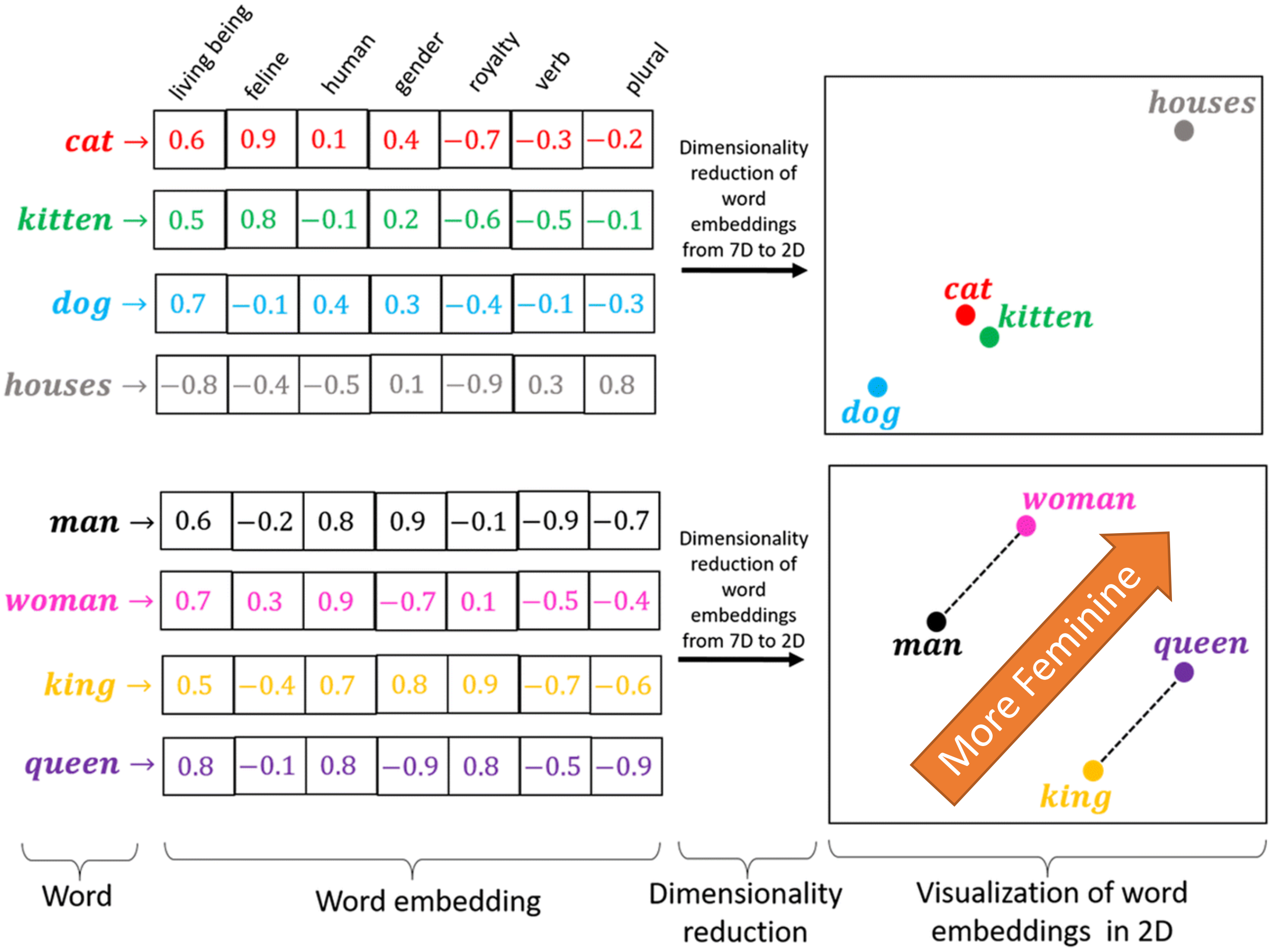
The **word "too"** could predict negative sentiment

Other methods: addressing weaknesses in BOW

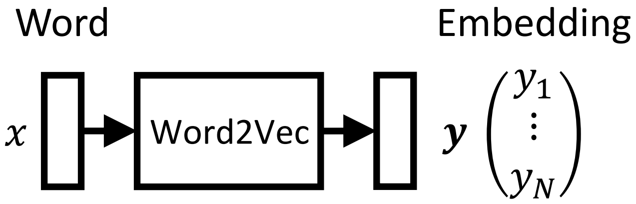
- Term frequency–inverse document frequency (TF-IDF)
  - Identifies if some words are generally **common** or **unique** to the instance
  - If **unique**, then word will be **more informative** to the class label
- N-grams
  - Adjacent words change meaning
  - e.g., "I am happy, not sad" vs. "I am sad, not happy"
    - But: BOW("I am happy, not sad") = BOW("I am sad, not happy")
    - With bigrams: BOW("I am happy, not_sad") ≠ BOW("I am sad, not_happy")
- Parts of Speech (POS) and Grammar
  - Structure of the sentence matters

You need to **understand** w.r.t. Bag-of-Words (BOW)
But you will **not** be tested about their technical approach in **exam**

Words → Concepts: Word Embeddings



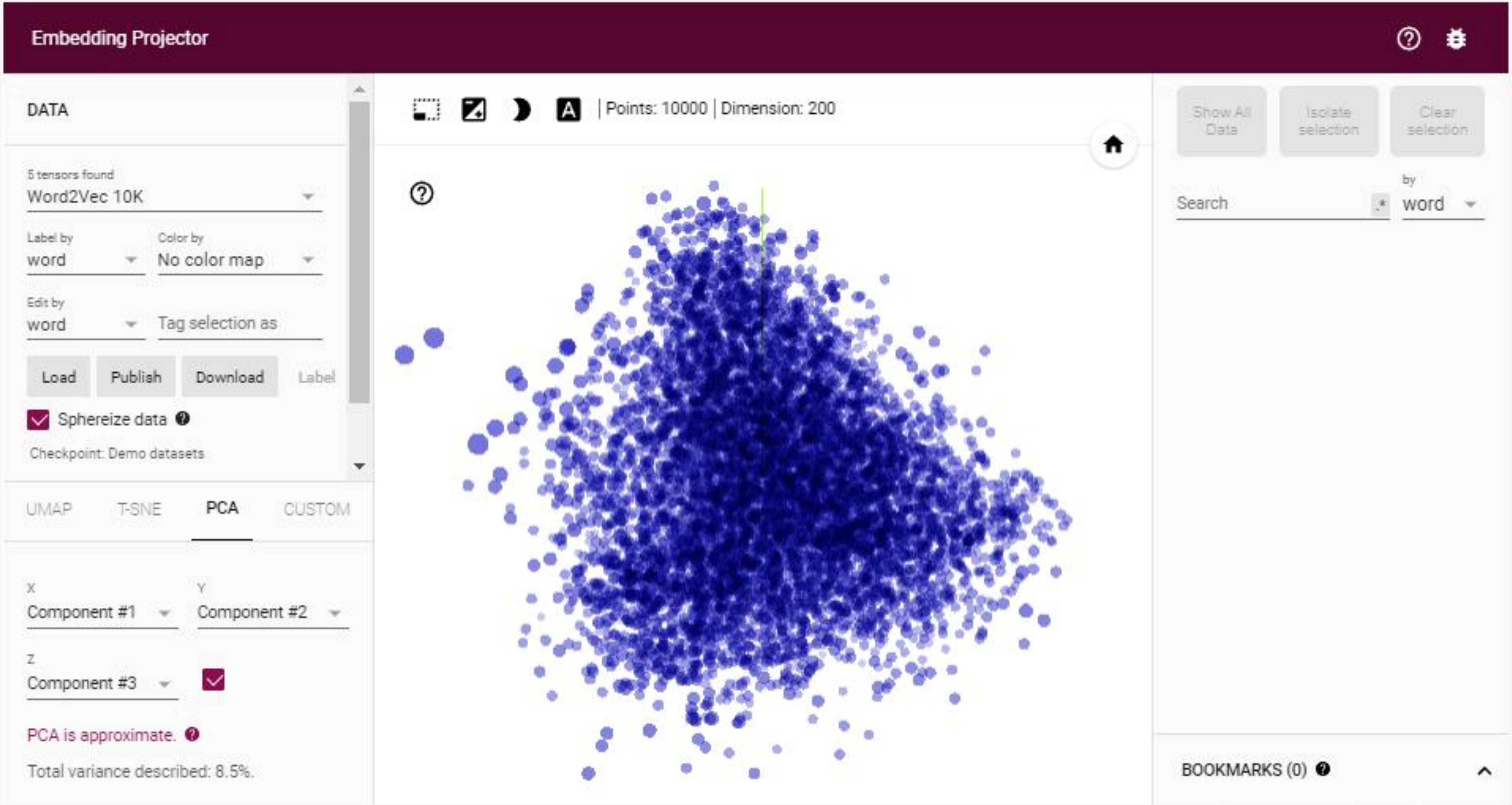
Not in exam



$$y = \begin{pmatrix} y_1 \\ \vdots \\ y_N \end{pmatrix}$$

https://www.tensorflow.org/tutorials/text/word2vec

Source: https://medium.com/@hari4om/word-embedding-d816f643140



Source: https://projector.tensorflow.org


Questions!

Wrapping Up

Department of Computer Science
School of Computing

What did we learn?

1. Describe **issues** when extracting features for various data types
2. Describe **techniques** of feature extraction/engineering for different data types

Tabular	Temporal	Image	Text
• Domain-specific custom equations • Features from counting, aggregation, difference, min, max	• Features from previous values, aggregate statistics, linear regression • Wave analysis features	• RGB image as 3D tensor • Color features from RGB histogram • Shape features from edge detection • Edge detection via Convolution	• Tokenization • Stemming, Lemmatization • Stop words • Bag-of-Words encoding

Useful Programming Libraries for Feature Extraction

- General / Tabular (pandas, NumPy, scikit-learn)
- Images / Computer Vision (OpenCV, Pillow/PIL, scikit-image)
- Text / Natural Language (NLTK, CoreNLP, spaCy)
- Temporal / Time Series (tsfresh)

Credit: Joseph Gonzalez, John DeNero, Josh Hug

Next week:

Perceptron and Neural Networks

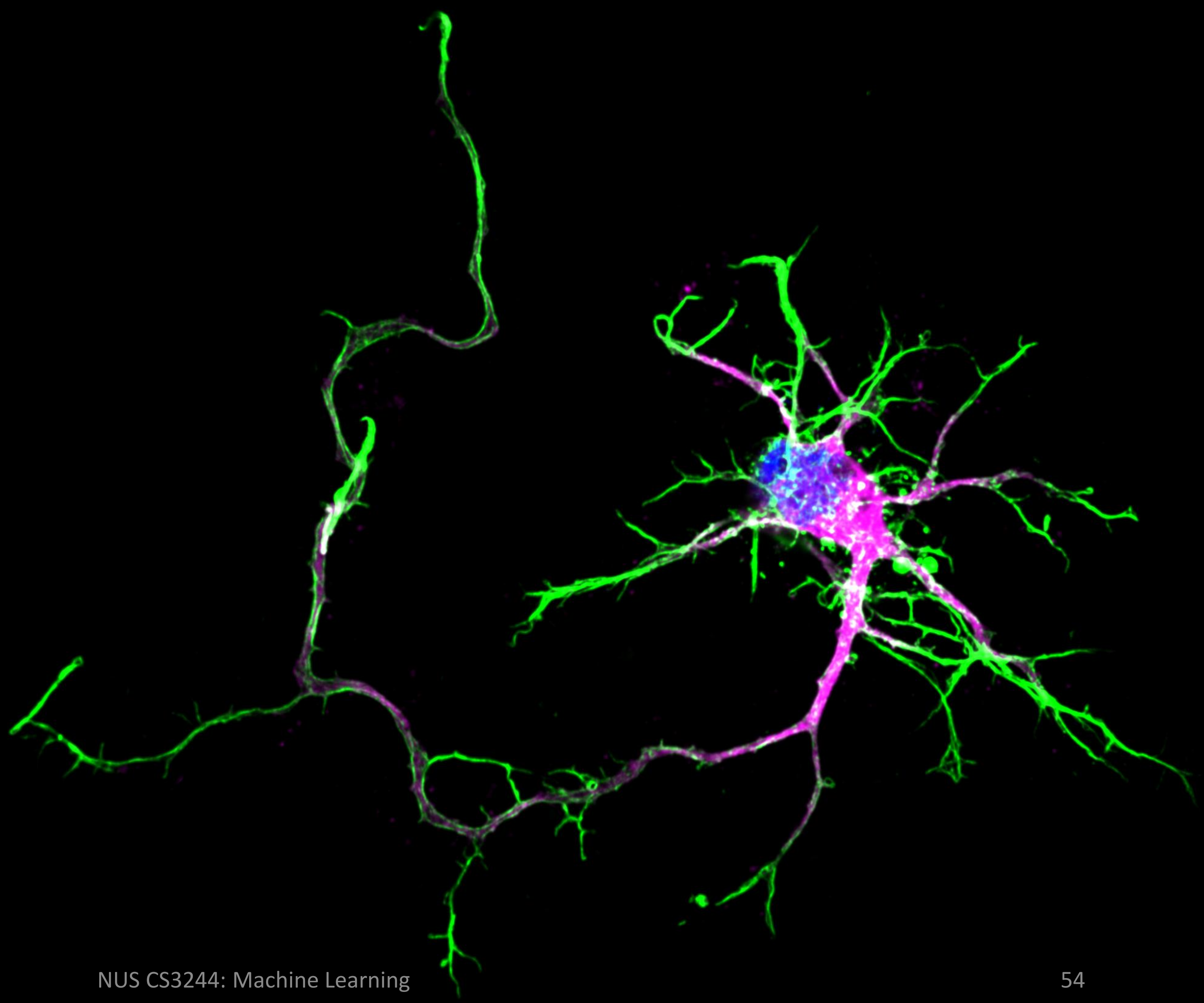


Image credit: https://cellmig.org/gallery/

W09 Pre-Lecture Task (due before next Mon)

Watch

1. But what is a neural network? | Chapter 1, Deep learning (~20 min) by 3Blue1Brown
2. The Nervous System, Part 1: Crash Course A&P #8 (~10 min) by CrashCourse

Discuss

1. Reflect on how **artificial** neural networks are different from **human** neural networks.
2. Identify **one** point (no need to write several).
3. Post a 1–2 sentence answer to the topic in your tutorial group: #tg-xx