# Copyright Notice

DeepLearning.AI

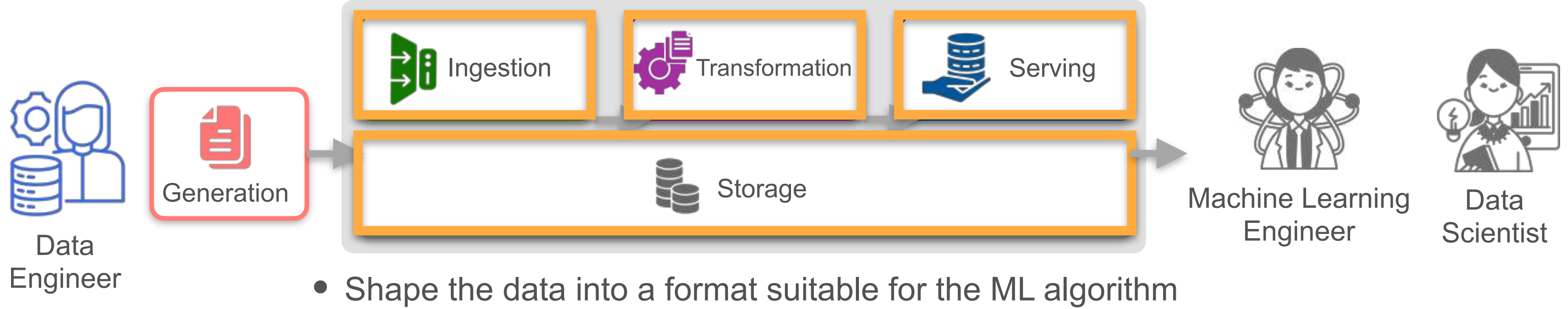
# Data Transformation, Modeling and Serving

## Data Modeling and Transformation for Machine Learning

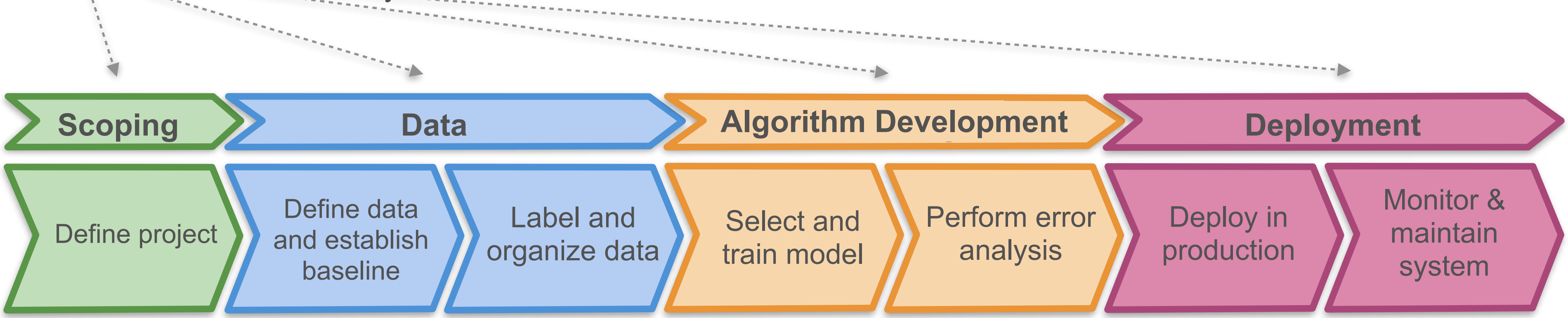
# Data Modeling and Transformation for Machine Learning

## Week 2 Overview

# Data Engineering for Machine Learning




- Shape the data into a format suitable for the ML algorithm
- Maybe clean the data, convert it, or even create additional columns




**Machine Learning Project Lifecycle Framework**

# Data Engineer, Data Scientist and Machine Learning Engineer

Data Engineer

ML Engineer / Data Scientist

Separate teams

Data Engineer

ML Engineer / Data Scientist

Serve raw data

Process the raw data

Data Engineer

ML Engineer / Data Scientist

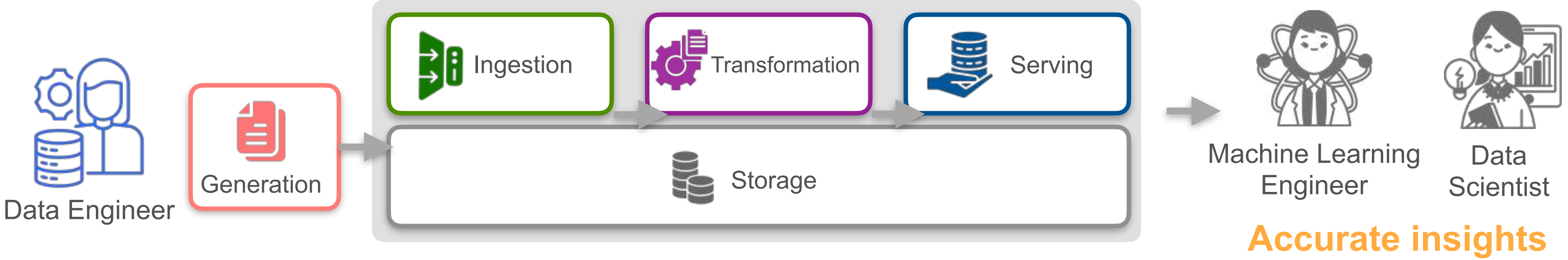
Process the raw data

Use the processed data for model training

Data Engineer

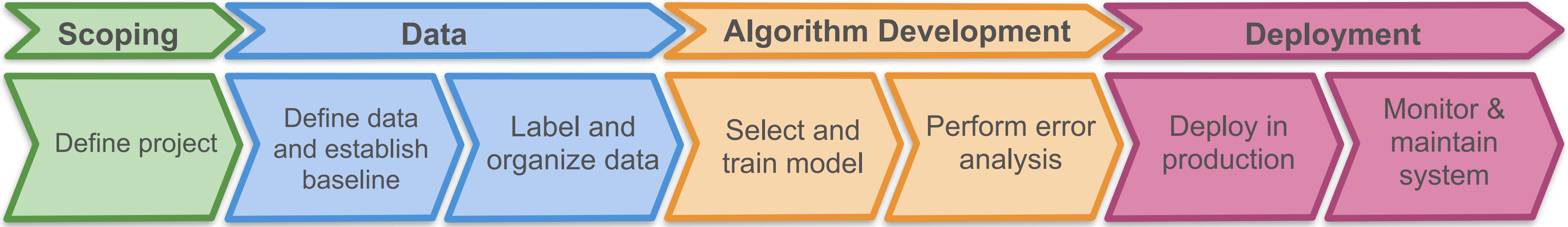
No mature ML team

Handle some extremely ML-specific tasks




Help organization adopt a **data-centric** approach to ML:

- Enhance the ML system by collecting high-quality data
- “Garbage in, garbage out”




**Machine Learning Project Lifecycle Framework**

# This Week's Plan

- ML terminology and the the Machine Learning Project Lifecycle

Tabular

- How to structure tabular data for classical ML algorithms

Image

- How to prepare image data for classical and advanced ML algorithms

Text

- How to preprocess text data and transform text into vectors
  (Manually processing text to meet specific cost and system requirements)

# Modeling and Processing Tabular Data for Machine Learning

## Machine Learning Overview

## ML System 1

## ML System 2

## ML System 3

## ML System 1 Predict customer churn

Customer demographic | Browsing history | Historical sales & product data | Customer churn data

Features

Labels

Learn

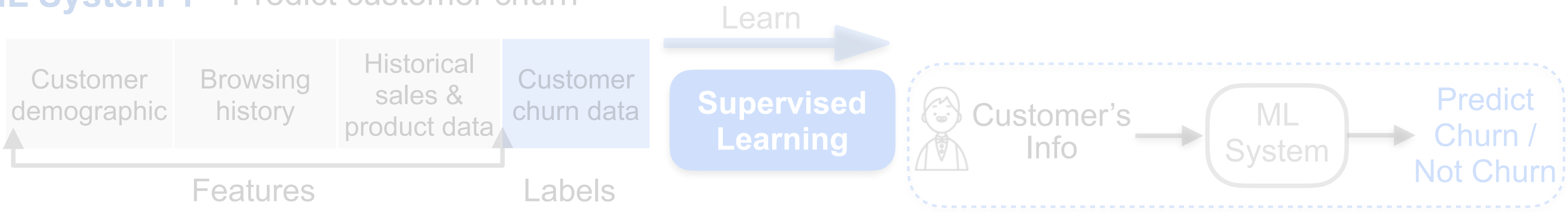
**Supervised Learning**

Customer's Info → ML System → Predict Churn / Not Churn

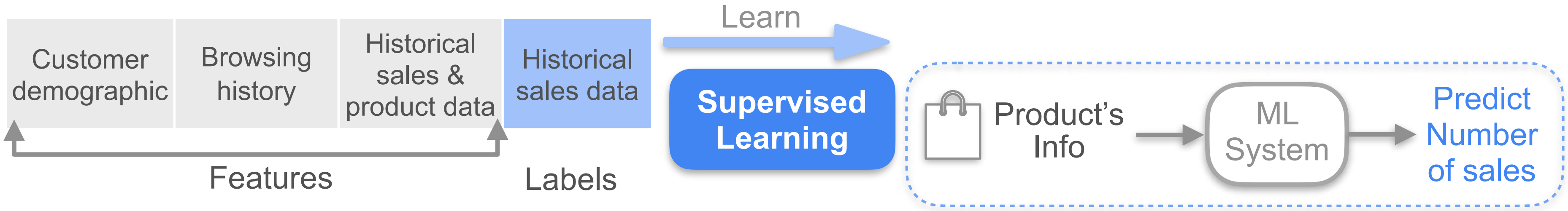
## ML System 2

## ML System 3

## ML System 1 Predict customer churn




## ML System 2 Predict the sales for the next new year holiday




## ML System 3

## ML System 1 Predict customer churn

| Customer demographic | Browsing history | Historical sales & product data | Customer churn data |
|---|---|---|---|

Features Labels

Learn → **Supervised Learning**

Classification

Categorical label

Customer's Info → ML System → Predict Churn / Not Churn

## ML System 2 Predict the sales for the next new year holiday

| Customer demographic | Browsing history | Historical sales & product data | Historical sales data |
|---|---|---|---|

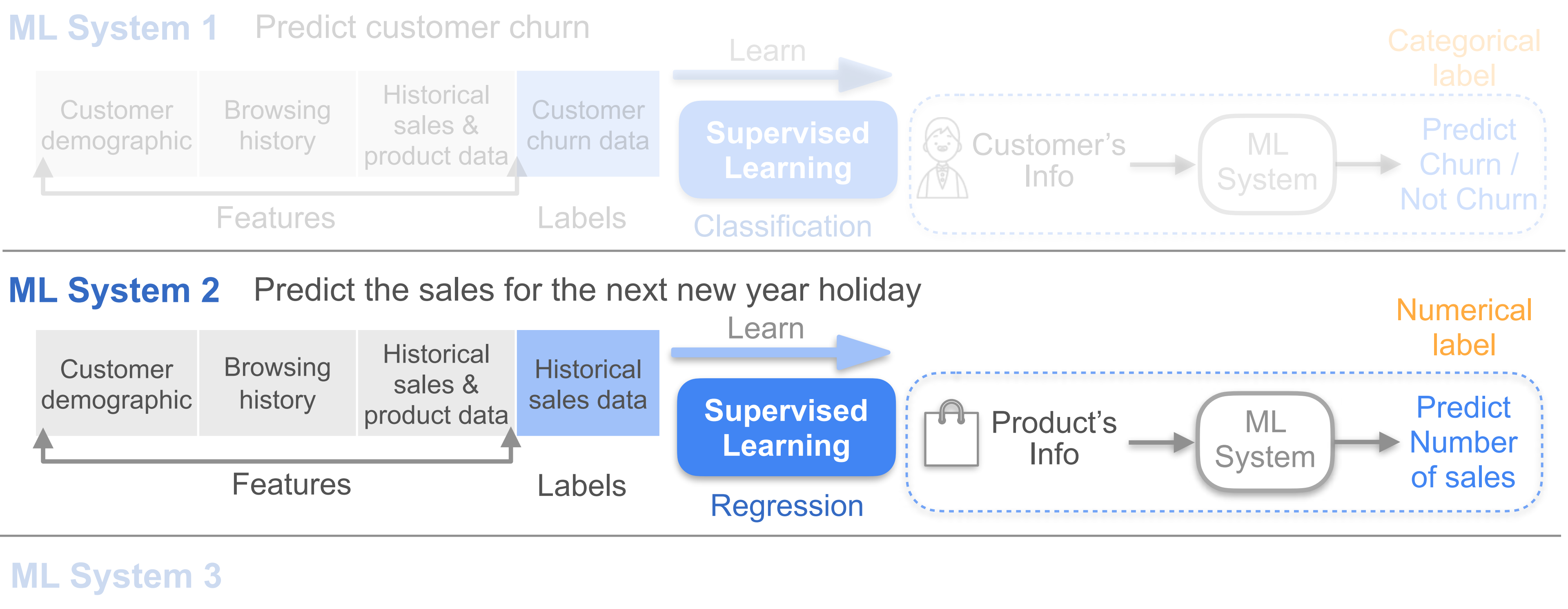
Features Labels

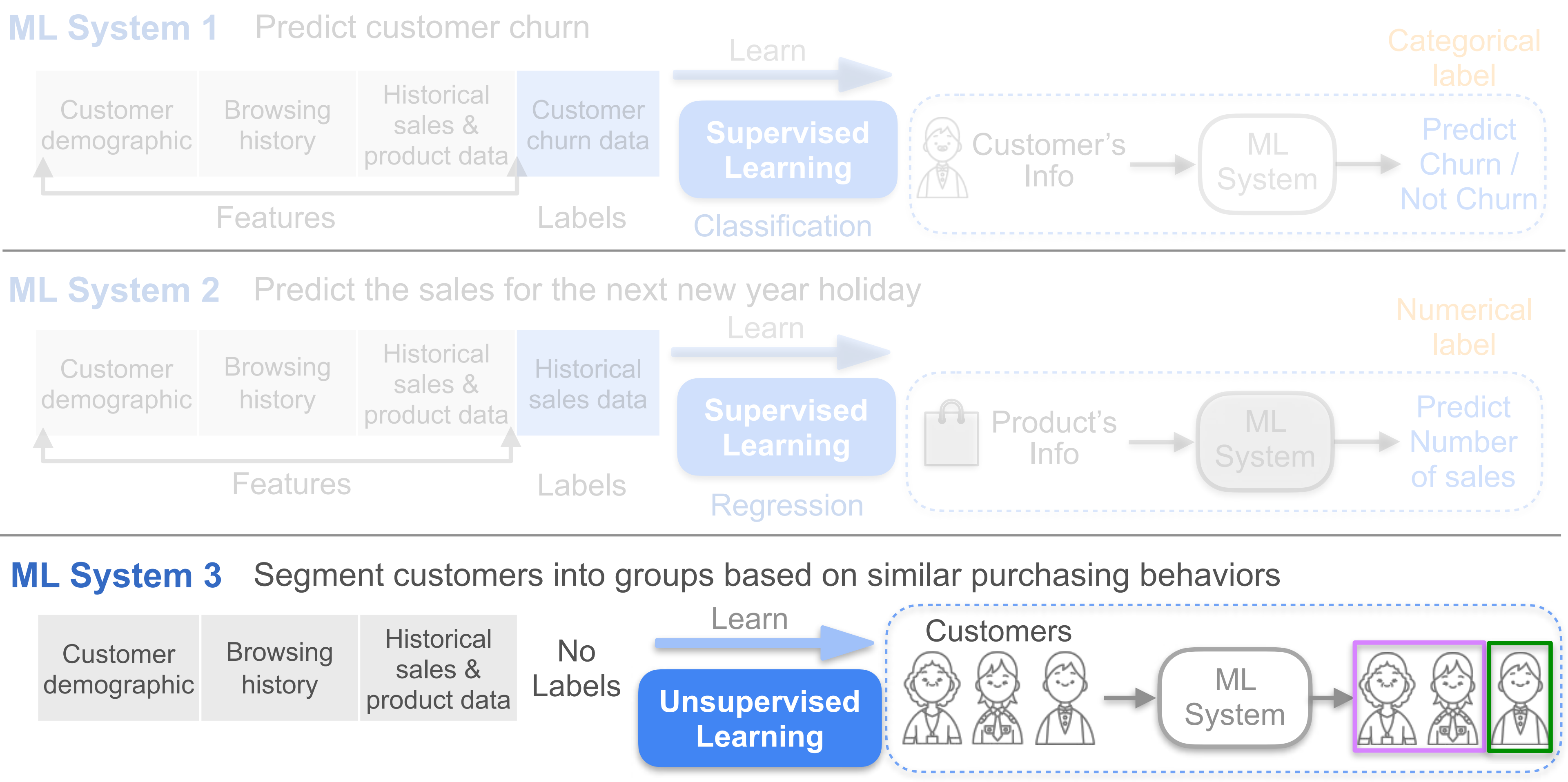
Learn → **Supervised Learning**



Product's Info → ML System → Predict Number of sales

## ML System 3

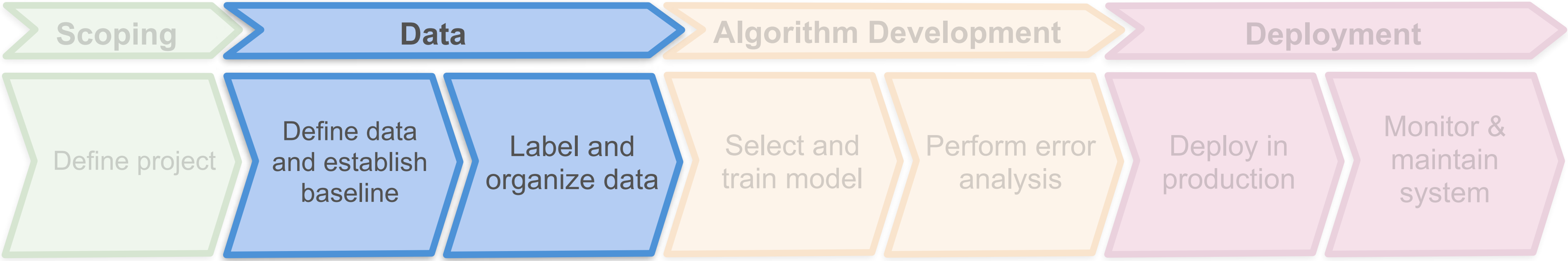

ML System 1
Predict customer churn
Customer demographic
Browsing history
Historical sales & product data
Customer churn data
Features
Labels
Learn
Supervised Learning
Classification
Categorical label
Customer's Info
ML System
Predict Churn / Not Churn
ML System 2
Predict the sales for the next new year holiday
Customer demographic
Browsing history
Historical sales & product data
Historical sales data
Features
Labels
Learn
Supervised Learning
Regression
Numerical label
Product's Info
ML System
Predict Number of sales
ML System 3


ML System 1
Predict customer churn
Customer demographic
Browsing history
Historical sales & product data
Customer churn data
Features
Labels
Learn
Supervised Learning
Classification
Categorical label
Customer's Info
ML System
Predict Churn / Not Churn
ML System 2
Predict the sales for the next new year holiday
Customer demographic
Browsing history
Historical sales & product data
Historical sales data
Features
Labels
Learn
Supervised Learning
Regression
Numerical label
Product's Info
ML System
Predict Number of sales
ML System 3
Segment customers into groups based on similar purchasing behaviors
Customer demographic
Browsing history
Historical sales & product data
No Labels
Learn
Unsupervised Learning
Customers
ML System

**Scoping** | Data | Algorithm Development | Deployment

**Define project** | Define data and establish baseline | Label and organize data | Select and train model | Perform error analysis | Deploy in production | Monitor & maintain system

ML Engineer /
Data Scientist




Determine what features and labels you need to collect

Data Engineer

Scoping | Data | **Algorithm Development** | Deployment

Define project | Define data and establish baseline | Label and organize data | **Select and train model** | **Perform error analysis** | Deploy in production | Monitor & maintain system

Split the data into:

- training set
- test set

Use the training set to train several ML algorithms

**Classical ML algorithms:**

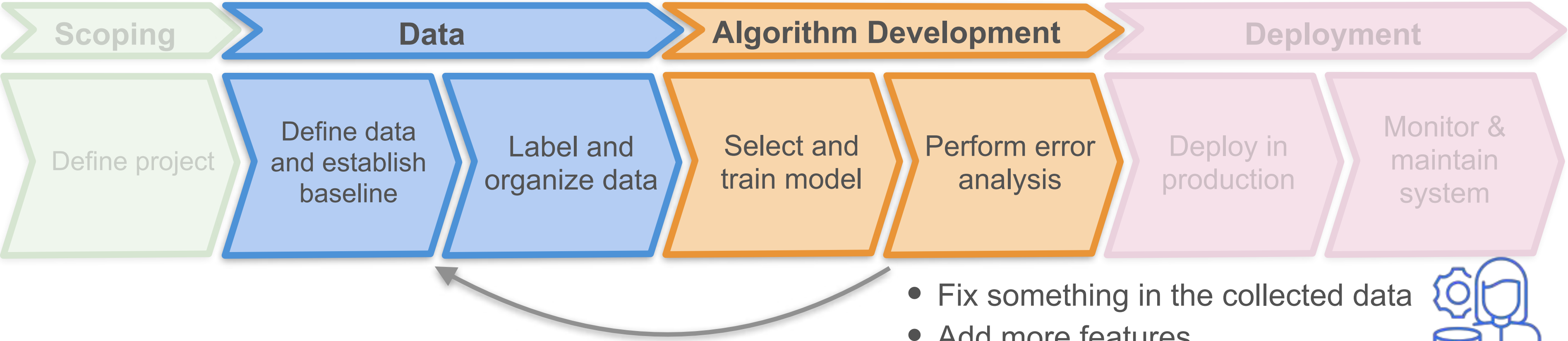
- Linear regression
- Logistic regression
- Decision trees
- Random forest and boosted trees

**Complex ML algorithms:**

- Deep neural networks
- Convolutional neural networks
- Recurrent neural networks
- Large language models

Select the best model through cross-validation

Evaluate the model performance using the test set




- Fix something in the collected data
- Add more features
- Collect more data

Data Engineer

Split the data into:

- training set
- test set

Use the training set to train several ML algorithms

**Classical ML algorithms:**

- Linear regression
- Logistic regression
- Decision trees
- Random forest and boosted trees

**Complex ML algorithms:**

- Deep neural networks
- Convolutional neural networks
- Recurrent neural networks
- Large language models

Select the best model through cross-validation

Evaluate the model performance using the test set

Scoping | Data | Algorithm Development | **Deployment**

Define project | Define data and establish baseline | Label and organize data | Select and train model | Perform error analysis | **Deploy in production** | **Monitor & maintain system**

ML Engineer /
Data Scientist

- Check to make sure the system's performance is good and reliable
- Write software to put system into production
- Monitor the system, track data, and maintain system

Data Engineer

- Prepare and serve the data that is needed for the deployed model
- Serve an updated set of data to re-train and update the model

**Scoping** | **Data** | **Algorithm Development** | **Deployment**

Define project → Define data and establish baseline → Label and organize data → Select and train model → Perform error analysis → Deploy in production → Monitor & maintain system

Data Engineer

Set up the pipeline to serve data that supports these phases

# Modeling and Processing Tabular Data for Machine Learning

DeepLearning.AI

## Modeling Data for Traditional Machine Learning Algorithms

# Numerical Tabular Form

| | No. of items purchased | Date of last purchase | Customer income | Minutes on Platform | Account type | Churned |
|---|---|---|---|---|---|---|
| **Customer** | 14 | 7/5/2024 | $50,000 | 15 | Family | No |
| | 9 | 3/4/2024 | $40,000 | 13 | Platinum | Yes |
| | Null | 8/12/2024 | Null | Null | Null | Yes |
| | 2 | 8/24/2024 | Null | 35 | Basic | No |
| | … | … | … | … | … | … |

# Numerical Tabular Form

What most classical ML algorithms expect as training data

| No. of items purchased | Days since last purchase | Customer income | Minutes on Platform | Account type | Purchases per minute | Churned |
|---|---|---|---|---|---|---|
| 0.93 | 0.90 | 0.5 | 0.24 | 1 | 0.93 | 0 |
| 0.57 | 0.29 | 0.4 | 0.20 | 2 | 0.69 | 1 Churn |
| 0.07 | 0.03 | 0.35 | 0.64 | 0 | 0.06 | 0 Not Churn |
| … | … | … | … | … | … | … |

**Features** **Labels**

- No missing values or duplicate rows
- Each column consists of numerical values that are within a similar range

# Feature Engineering

**Feature Engineering**

Any change or processing done to a raw column, and any creation of new features

- Handling missing values
- Feature scaling
- Converting categorical columns into numerical ones
- Creating new columns by combining or modifying existing ones

# Handling Missing Values

**Understand why the values are missing and then determine the most appropriate way**

| No. of items purchased | Days since last purchase | Customer income | Minutes on Platform | Account type | Churned |
|---|---|---|---|---|---|
| 14 | 28 | $50,000 | 15 | Family | No |
| 9 | 9 | $40,000 | 13 | Platinum | Yes |
| Null | 12 | Null | Null | Null | Yes |
| 2 | 1 | Null | 35 | Basic | No |
| … | … | … | … | … | … |

- Delete the entire column or row (if there's no risk of losing valuable data)
- Impute the missing values with summary statistics
  - Replace missing values with the column mean or median
  - Replace missing values with values from a similar record

# Handling Missing Values

**Understand why the values are missing and then determine the most appropriate way**

| No. of items purchased | Days since last purchase | Customer income | Minutes on Platform | Account type | Churned |
|---|---|---|---|---|---|
| 14 | 28 | $50,000 | 15 | Family | No |
| 9 | 9 | $40,000 | 13 | Platinum | Yes |
| 2 | 1 | $35,000 | 35 | Basic | No |
| … | … | … | … | … | … |

- Delete the entire column or row (if there's no risk of losing valuable data)
- Impute the missing values with summary statistics
  - Replace missing values with the column mean or median
  - Replace missing values with values from a similar record

# Scaling Numerical Features

**Scale features so that the values of each feature end up within a similar range**

| No. of items purchased | Days since last purchase | Customer income | Minutes on Platform | Account type | Churned |
|---|---|---|---|---|---|
| 14 | 28 | $50,000 | 15 | Family | No |
| 9 | 9 | $40,000 | 13 | Platinum | Yes |
| 2 | 1 | $35,000 | 35 | Basic | No |
| … | … | … | … | … | … |

- Training an ML algorithm is based on solving an optimization problem:
  - If values vary drastically → take longer for the optimization algorithm to converge
- Certain ML algorithms are based on distance metrics:
  - Their accuracies can be affected by different ranges of values

# Scaling Numerical Features

**Scale features so that the values of each feature end up within a similar range**

| No. of items purchased | Days since last purchase | Customer income | | | rned |
|---|---|---|---|---|---|
| 14 | 28 | 0.5 | | | lo |
| 9 | 9 | 0.4 | | | es |
| 2 | 1 | $35,000 | | | lo |
| … | … | … | … | … | … |

$$\frac{\$50{,}000 - \$0}{\$100{,}000 - \$0} = 0.5$$

$$\frac{\$40{,}000 - \$0}{\$100{,}000 - \$0} = 0.4$$

Min: $0
Max: $100,000

## Standardization

$$\frac{\text{value - column mean}}{\text{column standard deviation}}$$

Resulting value has mean of 0 and variance of 1

## Min-Max Scaling

$$\frac{\text{value - column min}}{\text{column max - column min}}$$

Resulting value is between 0 and 1

# Converting Categorical Columns into Numerical Ones

| No. of items purchased | Days since last purchase | Customer income | Minutes on Platform | Account type | Churned |
|---|---|---|---|---|---|
| 14 | 28 | 0.5 | 15 | Family | No |
| 9 | 9 | 0.4 | 13 | Platinum | Yes |
| 2 | 1 | 0.35 | 35 | Basic | No |
| … | … | … | … | … | … |

**One Hot Encoding**

| Account type |
|---|
| Family |
| Platinum |
| Basic |
| … |

→

| Basic | Family | Platinum |
|---|---|---|
| 0 | 1 | 0 |
| 0 | 0 | 1 |
| 1 | 0 | 0 |
| … | … | … |

**Ordinal Encoding**

| | Account type |
|---|---|
| middle | Family |
| most expensive | Platinum |
| cheapest | Basic |
| | … |

→

| Account type |
|---|
| 2 |
| 3 |
| 1 |
| … |

**Embeddings**

More on this later

DeepLearning.AI

# Modeling and Processing Tabular Data for Machine Learning

## Processing Tabular Data for Classical Machine Learning Algorithms Using Scikit-Learn (Part 1)

Install User Guide API Examples Community More 1.5.0 (stable)

# scikit-learn

*Machine Learning in Python*

Getting Started | Release Highlights for 1.5

- Simple and efficient tools for predictive data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- ...ble - BSD license

Two Processing Methods:

- Standardization for the numerical columns
- One-hot encoding for the categorical columns

## Classification

Identifying which category an object belongs to.

**Applications:** Spam detection, image recognition.
**Algorithms:** Gradient boosting, nearest neighbors, random forest, logistic regression, and more...

Predicting a continuous-valued attribute associated with an object.

**Applications:** Drug response, stock prices.
**Algorithms:** Gradient boosting, nearest neighbors, random forest, ridge, and more...

Automatic grouping of similar objects into sets.

**Applications:** Customer segmentation, grouping experiment outcomes.
**Algorithms:** k-Means, HDBSCAN, hierarchical clustering, and more...

# Download Dataset

| CustomerID | Age | Tenure | Usage Frequency | Support Calls | Payment Delay | Subscription Type | Contract Length | Total Spend | Last Interaction | Churn |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 22 | 25 | 14 | 4 | 27 | Basic | Monthly | 598 | 9 | 1 |
| 2 | 41 | 28 | 28 | 7 | 13 | Standard | Monthly | 584 | 20 | 0 |
| 3 | 47 | 27 | 10 | 2 | 29 | Annual | Annual | 757 | 21 | 0 |
| … | … | … | … | … | … | … | … | … | … | … |

https://www.kaggle.com/datasets/muhammadshahidazeem/customer-churn-dataset

# Preparing Data for Training a Machine Learning Model

ML Engineer Team

## Dataset

| CustomerID | Age | Tenure | Usage Frequency | Support Calls | Payment Delay | Subscription Type | Contract Length | Total Spend | Last Interaction | Churn |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 22 | 25 | 14 | 4 | 27 | Basic | Monthly | 598 | 9 | 1 |
| 2 | 41 | 28 | 28 | 7 | 13 | Standard | Monthly | 584 | 20 | 0 |
| 3 | 47 | 27 | 10 | 2 | 29 | Annual | Annual | 757 | 21 | 0 |
| … | … | … | … | … | … | … | … | … | … | … |

80%

20%

**Training Dataset**

Customer_id
Standardized numerical columns
One-hot encoded categorical columns

**Testing Dataset**

Customer_id
Standardized numerical columns
One-hot encoded categorical columns

# Preparing Data for Training a Machine Learning Model

## 1. Split the data into training and test sets

## 2. Process the training data

a. Numerical columns → standardize
b. Categorical columns → one hot encoding
c. Combine processed columns with the Customer ID into a Pandas data frame
d. Convert Pandas data frame into a parquet file

Makes it easier

## 3. Process the test data

a. Numerical columns → standardize
b. Categorical columns → one hot encoding
c. Combine processed columns with the Customer ID
d. Convert Pandas data frame into a parquet file

Use the same computed statistics used on the training set

DeepLearning.AI

# Modeling and Processing Tabular Data for Machine Learning

## Processing Tabular Data for Classical Machine Learning Algorithms Using Scikit-Learn (Part 2)

# Preparing Data for Training a Machine Learning Model

## 1. Split the data into training and test sets

## 2. Process the training data

a. Numerical columns → standardize
b. Categorical columns → one hot encoding
c. Combine processed columns with the Customer ID into a Pandas data frame
d. Convert Pandas data frame into a parquet file

## 3. Process the test data

a. Numerical columns → standardize
b. Categorical columns → one hot encoding
c. Combine processed columns with the Customer ID
d. Convert Pandas data frame into a parquet file

# Modeling and Processing Unstructured Data for Machine Learning

## Modeling Image Data for Machine Learning Algorithms

# Training an ML Algorithm on Image Data

## Traditional ML algorithms

| No. of items purchased | Days since last purchase | Customer income | Minutes on Platform | Account type | Purchases per minute | Churned |
|---|---|---|---|---|---|---|
| 0.93 | 0.90 | 0.5 | 0.24 | 1 | 0.93 | 0 |
| 0.57 | 0.29 | 0.4 | 0.20 | 2 | 0.69 | 1 |
| 0.07 | 0.03 | 0.35 | 0.64 | 0 | 0.06 | 0 |
| … | … | … | … | … | … | … |

| | | | |
|---|---|---|---|
| 77 | … | … | … |
| … | … | … | … |
| … | … | … | … |
| … | … | … | … |
| … | … | … | 22 |

| | | | |
|---|---|---|---|
| 153 | … | … | … |
| … | … | … | … |
| … | … | … | … |
| … | … | … | … |
| … | … | … | 225 |

| | | | |
|---|---|---|---|
| 249 | … | … | … |
| … | … | … | … |
| … | … | … | … |
| … | … | … | … |
| … | … | … | 172 |

→ Train a traditional ML algorithm

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 77 | … | … | … | … | … | … | … | … | 22 |
| 153 | … | … | … | … | … | … | … | … | 225 |
| 249 | … | … | … | … | … | … | … | … | 172 |

- Lose spatial information that can be extracted from the relative location of pixels
- Can create a high-dimensional vector of features
  - e.g. 1000 pixels by 1000 pixels → vector of size 1 million
- Affect the performance of the ML algorithm

# Training an ML Algorithm on Image Data

## Convolutional Neural Network (CNN)

**Each layer tries to identify more image features to help with the ML task**

- First layer: Generic features
- Later layers: Complex patterns and textures

ML Engineer Team

- Start with pre-trained CNN algorithms
- Fine tune these models for the specific task

# Preparing Image Data for the Training an ML Algorithm

**Resizing**

**Flipping**

**Rotating**

Data Engineer

**TensorFlow**

**Scaling the pixels**

**Cropping**

**Adjusting brightness**

**Data Augmentation**

Technique used to create new versions of existing images

(Increases the size & variety of training data)

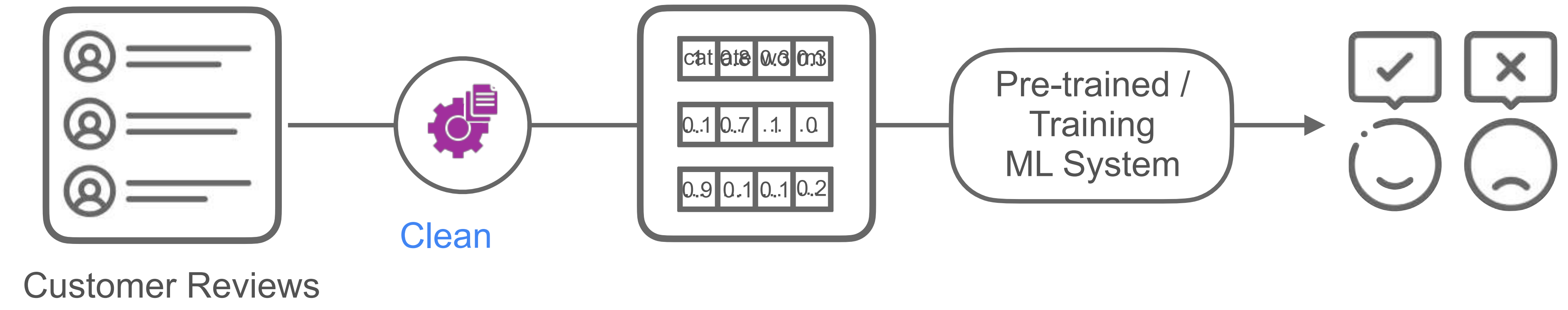
DeepLearning.AI

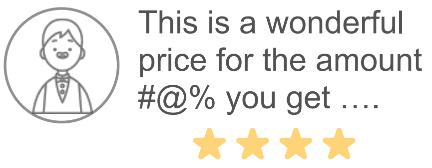
# Modeling and Processing Unstructured Data for Machine Learning

## Preprocessing Textual Data for Analysis and Text Classification

# Pre-processing Texts for ML

## Sentiment Analysis




**Depends on the type of ML algorithm:**

- Classical ML algorithm requires numerical data
- LLMs can work with tokens or words

# Pre-processing Texts for ML

# Processing Text

- **Cleaning**
- Normalization
- Tokenization
- Removal of Stop Words
- Lemmatization

Removing punctuations, extra spaces, characters that add no meaning

| Reviews | Cleaned Reviews |
| --- | --- |
| This is   a wonderful price for the amount #@% you get …. | This is a wonderful price for the amount you get |
| Great product! Big amt | Great product Big amt |
| I bought this for my son as his hair is thinning. I don't know yet how well is helping. He said the smell is great. | I bought this for my son as his hair is thinning I don't know yet how well is helping He said the smell is great |

# Processing Text

- Cleaning
- **Normalization**
- Tokenization
- Removal of Stop Words
- Lemmatization

Converting texts to consistent format:

- Transforming to lower-case
- Converting numbers or symbols to characters
- Expanding contractions

kg → kilograms

lbs → pounds

DE / D.E → data engineering

| Cleaned Reviews | Normalized Reviews |
|---|---|
| This is a wonderful price for the amount you get | this is a wonderful price for the amount you get |
| Great product Big amt → amount | great product big amount |
| I bought this for my son as his hair is thinning I don't know yet how well is helping He said the smell is great | i bought this for my son as his hair is thinning i do not know yet how well is helping he said the smell is great |

do not

# Processing Text

Cleaning

Normalization

**Tokenization**

Removal of Stop Words

Lemmatization

Splitting each review into individual tokens (words, subwords, short sentences)

| Normalized Reviews | Tokenized Reviews |
|---|---|
| this is a wonderful price for the amount you get | [this, is, a, wonderful, price, for, the, amount, you, get] |
| great product big amount | [great, product, big, amount] |
| i bought this for my son as his hair is thinning i do not know yet how well is helping he said the smell is great | [i, bought, this, for, my, son, as, his, hair, is, thinning, i, do, not, know, yet, how, well, is, helping, he, said, the, smell, is, great] |

Cleaning

Normalization

Tokenization

**Removal of Stop Words**

Lemmatization

# Processing Text

- Removing frequently used words such as “is”, “are”, “the”, “for”, “a”
- Define your own list of stop words
- Or use built-in set of NLP libraries

spaCy NLTK Gensim TextBlob

| Tokenized Reviews | Stop Words Removed |
| --- | --- |
| [this, is, a, wonderful, price, for, the, amount, you, get] | [this, wonderful, price, amount, you, get] |
| [great, product, big, amount] | [great, product, big, amount] |
| [i, bought, this, for, my, son, as, his, hair, is, thinning, i, do, not, know, yet, how, well, is, helping, he, said, the, smell, is, great] | [i, bought, this, my, son, his, hair, thinning, i, do, not, know, yet, how, well, helping, he, said, smell, great] |

Stop words: {is, a, for, the, as, are}

Cleaning

Normalization

Tokenization

Removal of Stop Words

**Lemmatization**

# Processing Text

Replacing each word with its base form or lemma (using NLP libraries)

getting / got → get

| Stop Words Removed |
|---|
| [this, wonderful, price, amount, you, get] |
| [great, product, big, amount] |
| [i, bought, this, my, son, his, hair, thinning, i, do, not, know, yet, how, well, helping, he, said, smell, great] |

| Tokenized and Lemmatized Reviews |
|---|
| [this, wonderful, price, amount, you, get] |
| [great, product, big, amount] |
| [i, buy, this, my, son, his, hair, thin, i, do, not, know, yet, how, well, help, he, say, smell, great] |

DeepLearning.AI

# Modeling and Processing Unstructured Data for Machine Learning

## Text Vectorization and Embedding

# Traditional Vectorization

**Bag of Words**

**Term-Frequency Inverse-Document-Frequency (TF-IDF)**

| Reviews |
|---|
| [this, wonderful, price, amount, you, get] → A document |
| [great, product, big, amount] |
| [I, buy, this, my, son, his, hair, thin, I, do, not, know, yet, how, well, help, he, say, smell, great] |

The corpus

The vocabulary

[this, wonderful, price, amount, you, get, great, product, big, I, buy, my, son, his, hair, thin, do, not, know, yet, how, well, help, he, say, smell]

| this | wonderful | price | amount | you | get | great | product | big | I | buy | my | son | his | hair | thin | do | not | not | know | yet | how | well | help | he | say | smell |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | | | | | | | | | | | | | | | | | | | | | | | | | | |

**Example**

"purchase" "buy" → High frequency, little meaning

"break" "exceptional" → Low frequency, more significant

**Bag of Words**

**Term-Frequency Inverse-Document-Frequency (TF-IDF)**

*Each entry: number of occurrences*

- Only takes into account the word frequency in each document
- Some frequently appearing words might carry little meaning

scikit learn

The corpus

| Reviews |
| --- |
| [this, wonderful, price, amount, you, get] → A document |
| [great, product, big, amount] |
| [I, buy, this, my, son, his, hair, thin, I, do, not, know, yet, how, well, help, he, say, smell, great] |

| this | wonderful | price | amount | you | get | great | product | big | I | buy | my | son | his | hair | thin | do | not | not | know | yet | how | well | help | he | say | smell |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 2 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

Bag of Words

**Term-Frequency Inverse-Document-Frequency (TF-IDF)**

*Account for the weight and rarity of each word*

**TF:** the number of times the term occurred in a document divided by the length of that document

**IDF:** how common or rare that word is in the entire corpus.

scikit learn

The corpus

| Reviews |
| --- |
| [this, wonderful, price, amount, you, get] → A document |
| [great, product, big, amount] |
| [I, buy, this, my, son, his, hair, thin, I, do, not, know, yet, how, well, help, he, say, smell, great] |

Bag of Words

**Term-Frequency Inverse-Document-Frequency (TF-IDF)**

*Account for the weight and rarity of each word*

**TF:** the number of times the term occurred in a document divided by the length of that document

**IDF:** how common or rare that word is in the entire corpus.

The corpus

| Reviews |
|---|
| [this, wonderful, price, amount, you, get] ⟶ A document |
| [great, product, big, amount] |
| [I, buy, this, my, son, his, hair, thin, I, do, not, know, yet, how, well, help, he, say, smell, great] |

| this | wonderful | price | amount | you | get | great | product | big | I | buy | my | son | his | hair | thin | do | not | not | know | yet | how | well | help | he | say | smell |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.33 | 0.44 | 0.44 | 0.33 | 0.44 | 0.44 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0.43 | 0 | 0 | 0.43 | 0.56 | 0.56 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.16 | 0 | 0 | 0 | 0 | 0 | 0.16 | 0 | 0 | 0.43 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 | 0.22 |

# Word Embedding

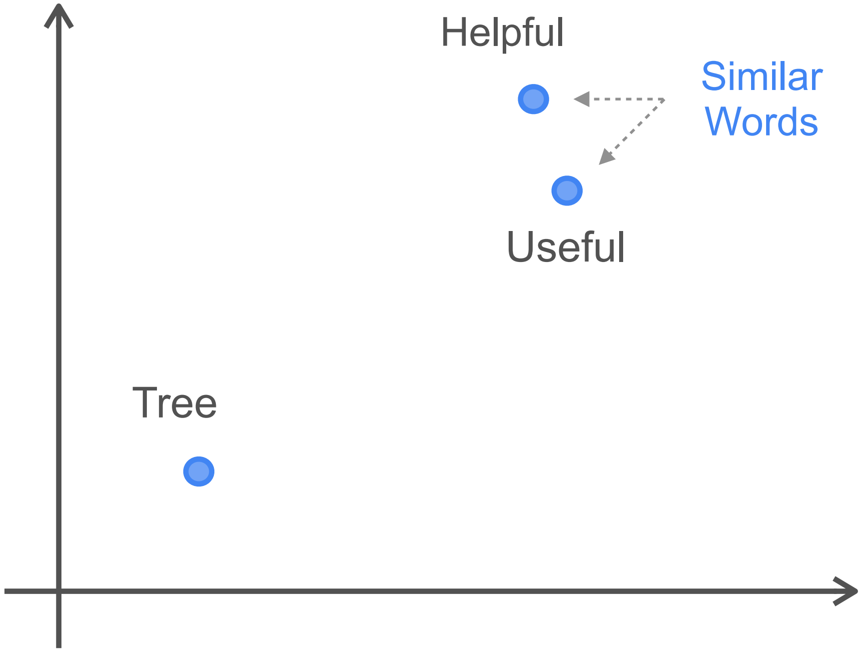
**Word**

**word2vec, GLOVE**

Trained to learn the embeddings of words from their co-occurrences

**Word Embedding**

Vector that captures the semantics meaning of the word



# Word Embedding

| Reviews |
| --- |
| [this, wonderful, price, amount, you, get] |
| [great, product, big, amount] |
| [I, buy, this, my, son, his, hair, thin, I, do, not, know, yet, how, well, help, he, say, smell, awesome] |

**Represent each review, not just each word, by one vector**

Word Embedding (great)
+
Word Embedding (product)
+
Word Embedding (big)
+
Word Embedding (amount)

→ **Vector that represents the sentence**

Does not account for the position of the words in the sentence

“A man ate a snake” ≠ “A snake ate a man”

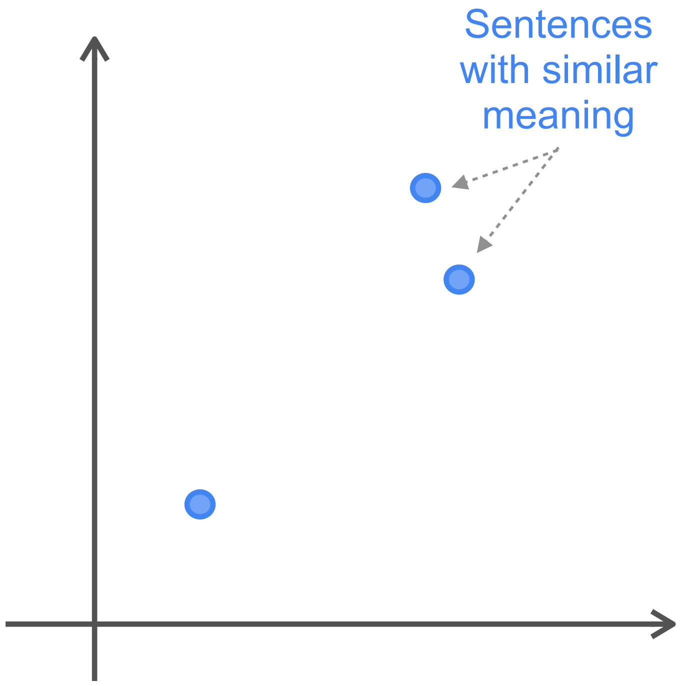
# Sentence Embedding

**Sentence**

**Pre-trained NLP models**

**Sentence Embedding**

- Vector that reflects the semantic meaning of the sentence
- Lower dimension than the vector generated by TF-IDF



# Sentence Embedding

**Sentence**

**Pre-trained NLP models**

based on Large Language Models (LLM)

**Open-Source**

SBERT.net

Sentence Transformers

**Closed-Source**

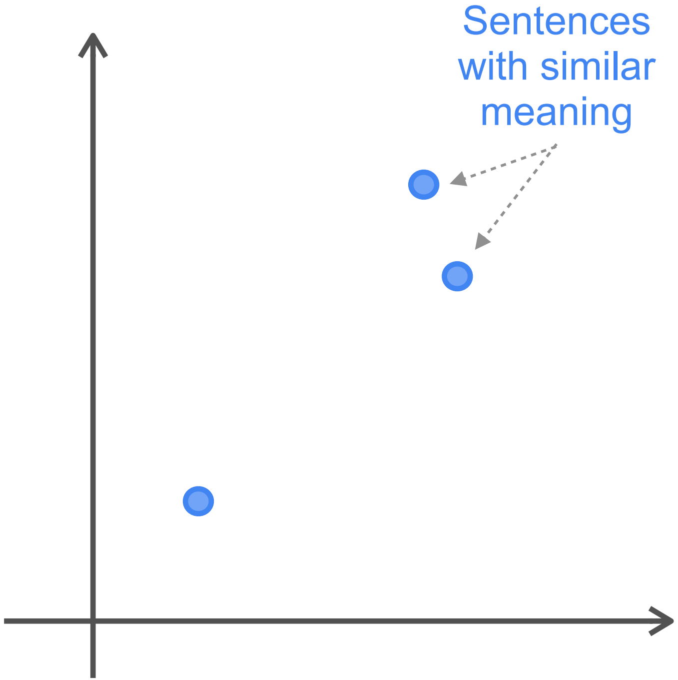
OpenAI

AI

Gemini

**Sentence Embedding**

- Vector that reflects the semantic meaning of the sentence
- Lower dimension than the vector generated by TF-IDF



# Sentence Embeddings

Text Reviews

↓

Embeddings

↙ ↘

Features to train an ML algorithm

Clustering, Similarity Search

DeepLearning.AI

# Data Modeling and Transformation for Machine Learning

## Week 2 Summary

# Tabular Data for Training an ML Algorithm

**Raw Data**

| | | | |
|---|---|---|---|
| Small | 4000 | 0.9 | 0.04 |
| Large | 7000 | Null | 0.02 |
| Medium | 7000 | | 0.02 |

**Numerical Tabular Form**

| | | | |
|---|---|---|---|
| 0.2 | 0.4 | 0.9 | 0.4 |
| 0.6 | 0.7 | 0.5 | 0.2 |
| 0.5 | 0.7 | 0.1 | 0.2 |

ML System

1. Impute data or delete empty records/columns
2. Convert categorical columns to numerical ones
   - One hot encoding, Ordinal encoding, etc.
3. Scale the numerical features

Lab

scikit learn

# Image Data for Training an ML Algorithm

## Classical ML algorithms

Unroll the images in a long sequence of pixels

## Convolutional neural networks

- Pre-processing techniques:
  - Image reshaping
  - Image normalization
- Data augmentation:
  - Flipping
  - Rotation
  - Adding distortions

# Textual Data for Training an ML Algorithm