VICTORIA UNIVERSITY OF WELLINGTON TE HERENGA WAKA

COMP309/AIML421 — ML Tools and Techniques

Week 6-Tutorial

A3-Kaggle Competition

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(Thanks to Christian Raymond)

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Kaggle Competition
COMP309/AIML421

COMP309/AIML421 2024 Kaggle Competition

Can we classify music into genres?

COMP-309-24/Ass3

COMP 309 *Machine Learning Tools and Techniques*

Assignment 3: Kaggle Competition

20% of Final Mark — Due: 11:59pm Friday 13rd September 2024

1 Objectives

The goal of this assignment is to help you tie together all the concepts you have learnt in the first half of this course in the lectures and assignments. To aid you in completing this assignment, you should review the major aspects of the course that have been explored so far, such as:

- Data understanding, cleansing, and pre-processing,
- Machine learning concepts,
- CRISP-DM and pipelines in general,
- Feature manipulation, including feature selection, feature construction and imputation,
- Statistical design and analysis of results.

These topics are (to be) covered in Weeks 1–7. Research into online resources for AI is encouraged, where the rabbit-hole[1] will provide useful jumping off points for further exploration.

2 Question Description

If Music is a Place — then Jazz is the City, Folk is the Wilderness, Rock is the Road, Classical is a Temple.

Vera Nazarin

AIML-421-24/Ass3

AIML 421 — *Machine Learning Tools and Techniques*

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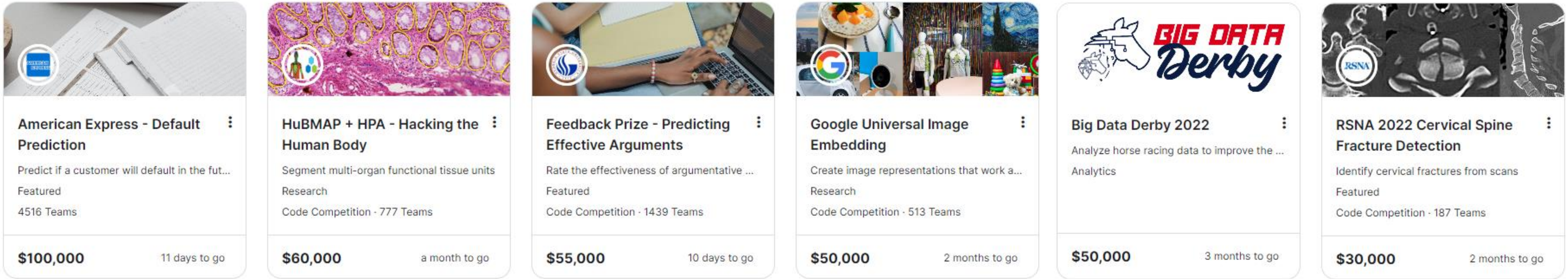
Kaggle Competition

Kaggle is a public competition platform for machine learning where companies upload their data and invite participants from all over the world to help build models.



https://www.kaggle.com/competitions

- The team who builds the most accurate model receive awards.
- Gain hands-on experience in constructing machine learning models.

Kaggle Competition

https://web.archive.org/web/20090924184639/http://www.netflixprize.com/community/viewtopic.php?id=1537

kaggle

Netflix Prize: A Kaggle competition for the best movie recommendation system for predicting user ratings for films, based on previous ratings.

- Grand **prize of $1,000,000 USD** was awarded (2009).
- Winners system had RMSE of 0.8567 on the testing set. Was a **10.06% improvement** over prior system.

Kaggle Competition

Overview Data Code Discussion Leaderboard Rules Join Competition ···

Leaderboard

Raw Data Refresh

Public Private

Prize Contenders

#	Team	Members		Score	Entries	Last	Code
1	Young for you			0.802	246	17h	
2	💳VISA💳			0.801	358	1h	
3	byDefault [JuneHomes]			0.801	310	8h	
4	Luck solo gold please			0.801	45	4d	
5	Mengfei Li			0.801	264	11h	

Public Leaderboard:
Score shown throughout the whole duration of the competition.

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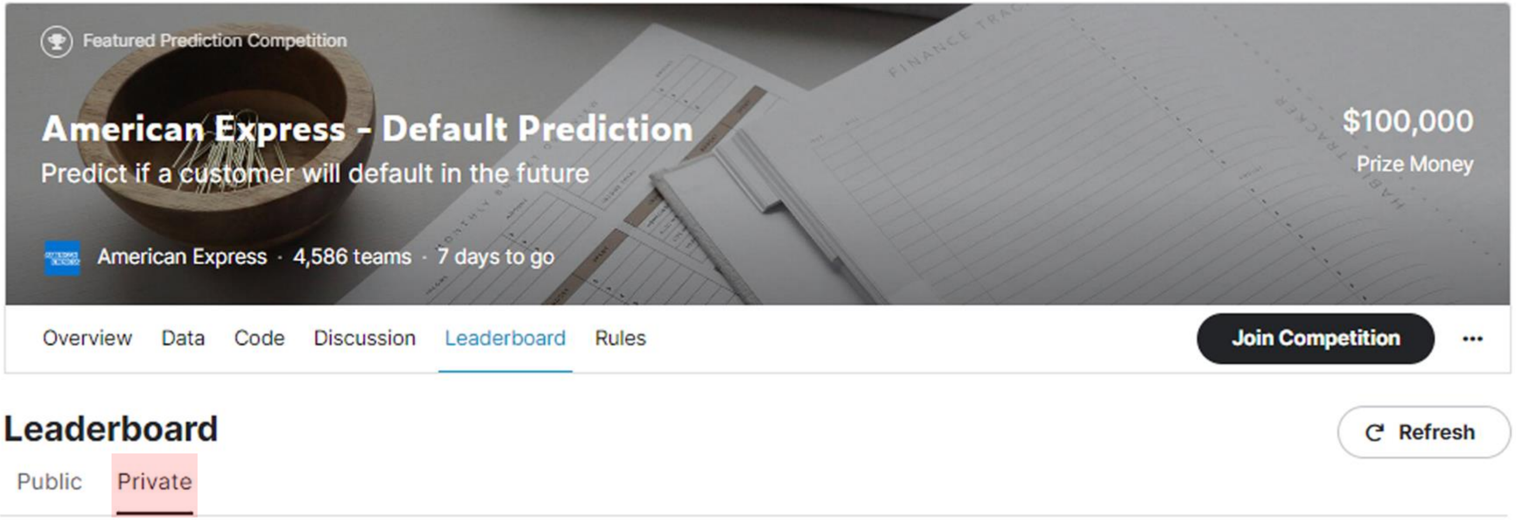
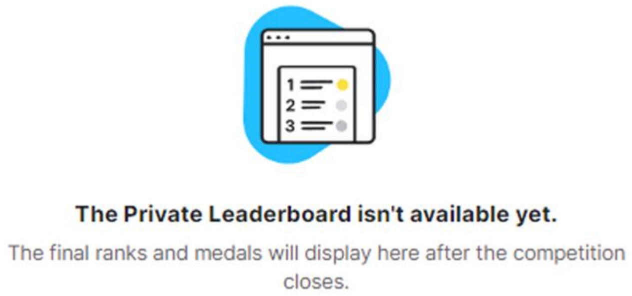
Kaggle Competition



Private Leaderboard:
Performance only shown at the end of the competition (after the due date)



The private leaderboard is what matters!

Kaggle Competition

This years Kaggle Competition: Music Genre Classification

Develop the best possible ML system to predict the genres of music. The task is to classify the music tracks into one of ten genres based on the provided audio features.

Overview

Tutorial going over relevant content for the in-class Kaggle competition (assignment 3)

Topics Covered:

- **Exploratory Data Analysis**
- **Data Pre-processing**
- **Machine Learning Modelling**
- **Model Evaluation and Validation**
- **Assignment Tips**

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Exploratory Data Analysis

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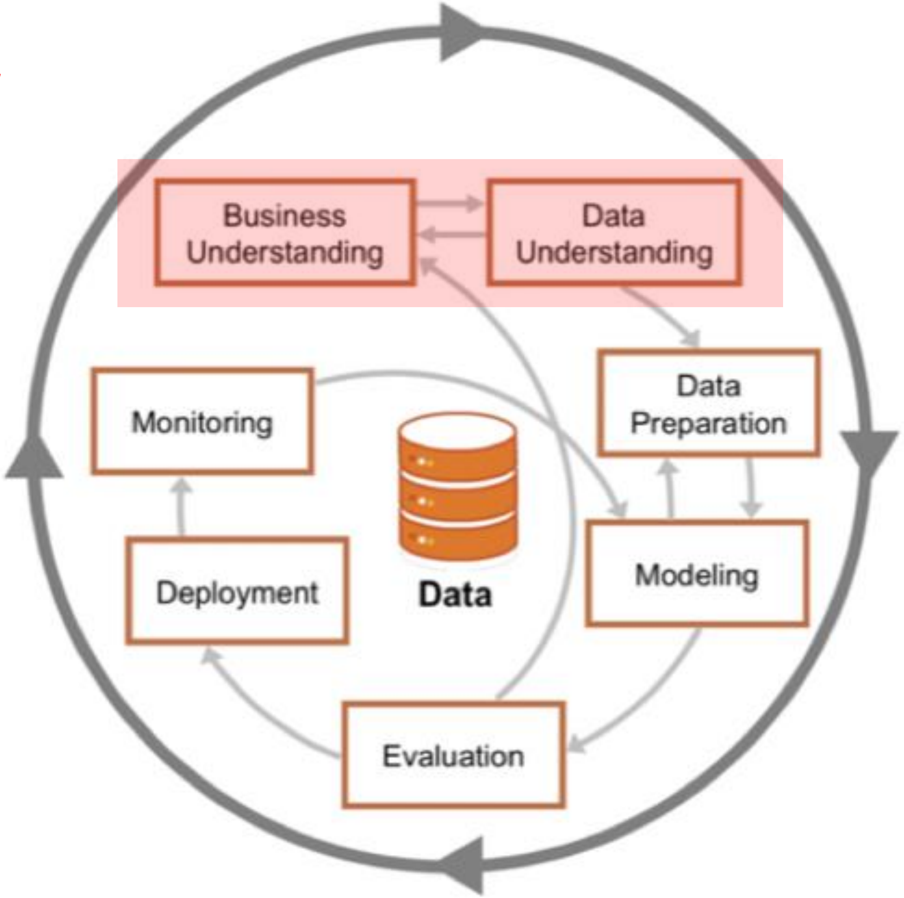
Business and Data Understanding

Before you do anything, you need to understand you data!

- **How many instances are in the dataset?**
- **How many features are in the dataset?**
- **What does each of the features represent?**

Kaggle Competitions are primarily won by good data pre-processing and data transformation. Need business and data understanding to inform our decisions.

Last year all the top submissions had reports which showed significant insight into the given data.



CRISP-DM Process

Kaggle Competition: Music Genre Classification

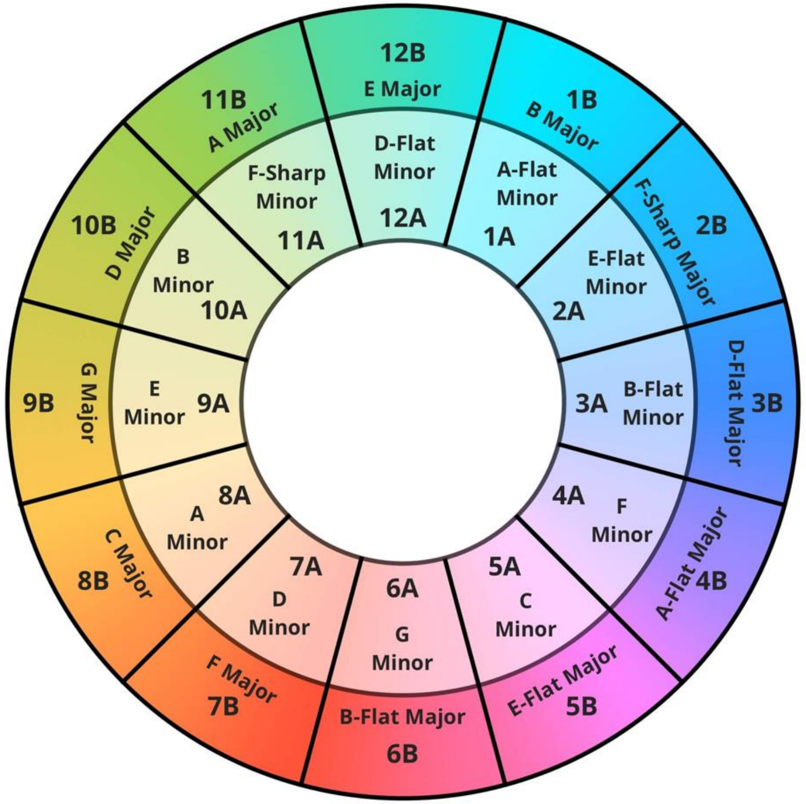
Three Example Instances:

	artist_name	track_name	track_id	popularity	acousticness	danceability	duration_ms
1	artist_name	track_name	track_id	popularity	acousticness	danceability	duration_ms
2	B.o.B	John Doe (feat. Priscilla)	5T2AwbeUDXYbhjiDrD0s3e	48	0.239	0.722	212006
3	Prince Royce	Back It Up	0kCl6Aw5ikVtyQIvF4PwdO	49	0.0895	0.736	200936
4	Tamar Braxton	Let Me Know	28c4nfBHdb3xviamRCEsIe	47	0.0958	0.55	-1

…

…

energy	instrumentalness	key	liveness	loudness	mode	speechiness	tempo	time_signature	valence	genre
0.697	0	A#	0.062	-7.083	Major	0.0404	120.132	4-Apr	0.487	Dance
0.743	0	C#	0.0482	-7.437	Major	0.0758	?	4-Apr	0.799	Dance
0.667	0	D	0.138	-5.362	Major	0.0346	78.019	4-Apr	0.433	Dance



Key and Mode features may requires domain knowledge to properly encode the relationship in a way the model will understand.

- You aren't always given all the information about the data. Consult subject matter experts (SME) and do research!

Summary Statistics

Summarize a set of observations in order to communicate the largest amount of information as simply as possible.

- **Location:** Mean, Median, Mode
- **Spread:** Standard Deviation, Variance, Range
- **Shape:** Features Skew, Class distribution
- **Dependence:** Pearson's Correlation
- **Other:** Missing Values, Number of Features, Instances …

Don't reinvent the wheel! Libraries for Summary Statistics:

NumPy: https://numpy.org/doc/
Pandas: https://pandas.pydata.org/docs/
Statistics: https://docs.python.org/3/library/statistics.html

Helpful Functions

Syntax – Creating DataFrames

	a	b	c
1	4	7	10
2	5	8	11
3	6	9	12

```
df = pd.DataFrame(
          {"a" : [4 ,5, 6],
           "b" : [7, 8, 9],
           "c" : [10, 11, 12]},
        index = [1, 2, 3])
```

Specify values for each column.

```
df = pd.DataFrame(
     [[4, 7, 10],
      [5, 8, 11],
      [6, 9, 12]],
     index=[1, 2, 3],
     columns=['a', 'b', 'c'])
```

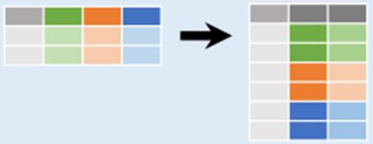
Specify values for each row.

n	v	a	b	c
d	1	4	7	10
	2	5	8	11
e	2	6	9	12

```
df = pd.DataFrame(
          {"a" : [4 ,5, 6],
           "b" : [7, 8, 9],
           "c" : [10, 11, 12]},
index = pd.MultiIndex.from_tuples(
          [('d',1),('d',2),('e',2)],
             names=['n','v']))
```

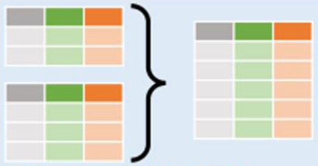
Create DataFrame with a MultiIndex

Reshaping Data – Change the layout of a data set



`pd.melt(df)`
Gather columns into rows.

`df.pivot(columns='var', values='val')`
Spread rows into columns.



`pd.concat([df1,df2])`
Append rows of DataFrames

`pd.concat([df1,df2], axis=1)`
Append columns of DataFrames

`df.sort_values('mpg')`
Order rows by values of a column (low to high).

`df.sort_values('mpg',ascending=False)`
Order rows by values of a column (high to low).

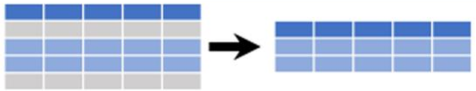
`df.rename(columns = {'y':'year'})`
Rename the columns of a DataFrame

`df.sort_index()`
Sort the index of a DataFrame

`df.reset_index()`
Reset index of DataFrame to row numbers, moving index to columns.

`df.drop(columns=['Length','Height'])`
Drop columns from DataFrame

Subset Observations (Rows)



`df[df.Length > 7]`
Extract rows that meet logical criteria.

`df.drop_duplicates()`
Remove duplicate rows (only considers columns).

`df.head(n)`
Select first n rows.

`df.tail(n)`
Select last n rows.

`df.sample(frac=0.5)`
Randomly select fraction of rows.

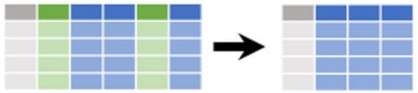
`df.sample(n=10)`
Randomly select n rows.

`df.iloc[10:20]`
Select rows by position.

`df.nlargest(n, 'value')`
Select and order top n entries.

`df.nsmallest(n, 'value')`
Select and order bottom n entries.

Subset Variables (Columns)



`df[['width','length','species']]`
Select multiple columns with specific names.

`df['width']` *or* `df.width`
Select single column with specific name.

`df.filter(regex='regex')`
Select columns whose name matches regular expression *regex*.

[Python Cheat Sheets]

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Basic Data Visualization

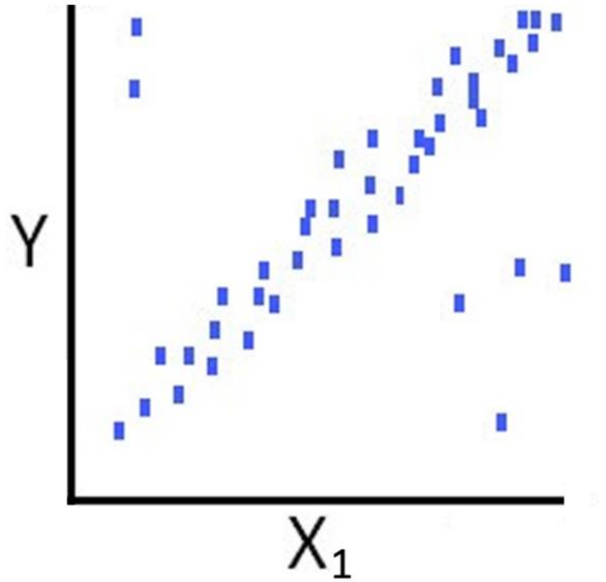
The graphical representation of information and data. Using visual elements like charts, graphs, and other data visualization tools to provide an accessible way to see and understand trends, and patterns in data.

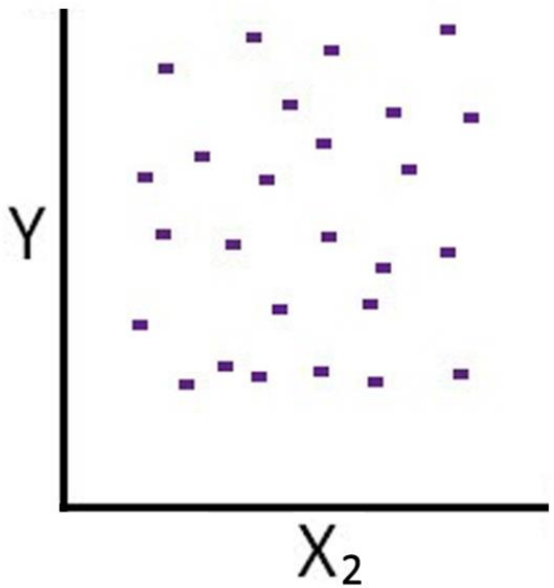
Start with a simple scatterplot!

Outlier Instances

Patterns

Skewed Data





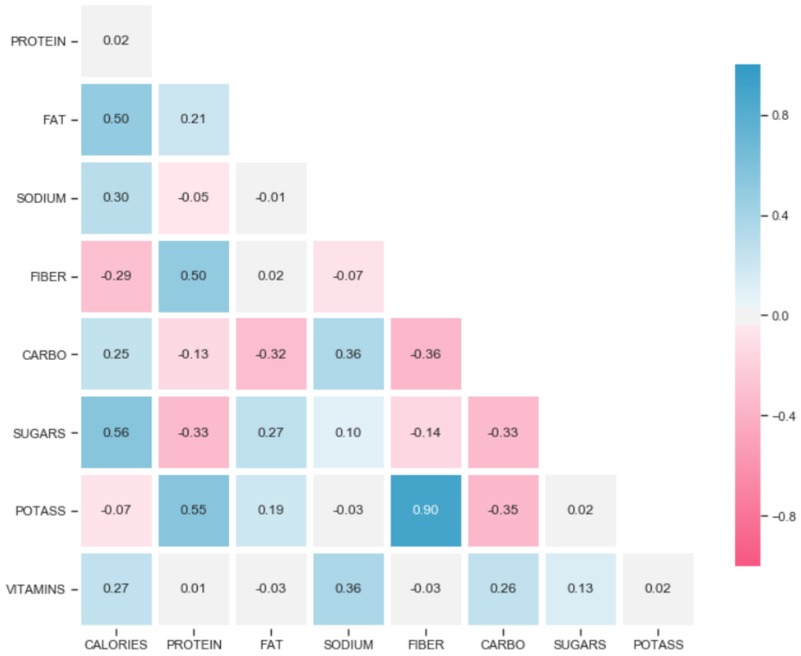
Important Features

Irrelevant Features

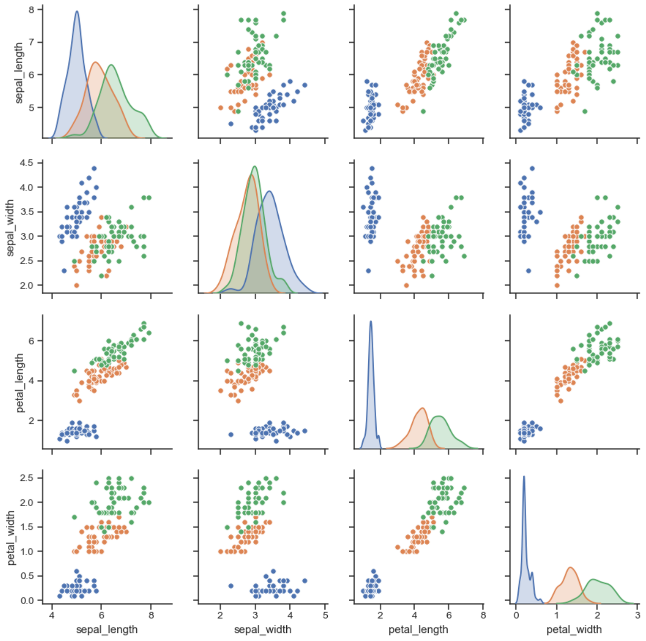
Anomalies In Data

Basic Data Visualization

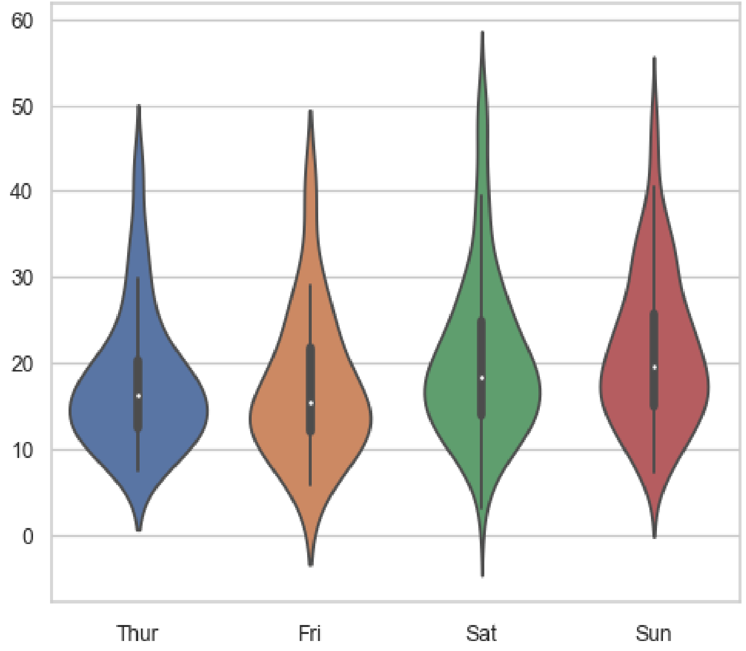
Correlation Heatmap



Scatter Matrix



Violin Plot



https://matplotlib.org/stable/plot_types/index.html
https://seaborn.pydata.org/examples/index.html

Identifying Missing Data

Missing data is not always easy to identify.

Different Types of Missing Data:

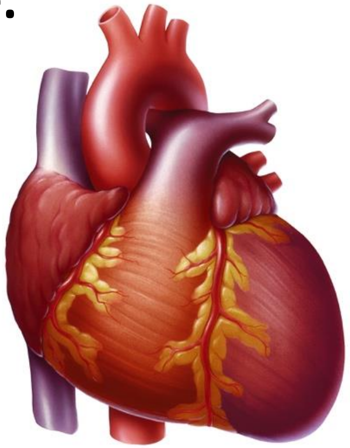
- Missing completely at random (MCAR)
- Missing at random (MAR)
- Missing not at random (MNAR)

More about this in week 7

Solution to Missing Data:

1. **Remove** the missing data instances from the dataset.
2. Use **imputation** methods to substitute the missing values.
3. Use a **model which incorporates them**.

Example:



Cardiovascular Dataset of Patients with Heart Condition

- Some patients had a Beats Per Minute (BPM) of 0
- Technician set some patients to 0 when they didn't record the BPM.

Data Preprocessing

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Feature Selection

The process of selecting a subset of relevant features for use in model construction.

Why should we perform Feature Selection?

1. Simplify the model and make it more interpretable
2. Reduce model training times
3. Remove redundant features
4. Remove irrelevant features

How to perform Feature Selection?

- Use domain knowledge and expertise (Manual)
- Use feature selection techniques (Automatic)
  - Three types: Filter, Wrapper, and Embedded

Titanic Dataset: Classify Live or Die

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Feature Selection

The process of selecting a subset of relevant features for use in model construction.

PassengerId	Survived	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
1	0	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
2	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
3	1	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
4	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
5	0	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
6	0	Moran, Mr. James	male	NaN	0	0	330877	8.4583	NaN	Q
7	0	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S
8	0	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.0750	NaN	S
9	1	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	female	27.0	0	2	347742	11.1333	NaN	S

Titanic Dataset: Classify Live or Die

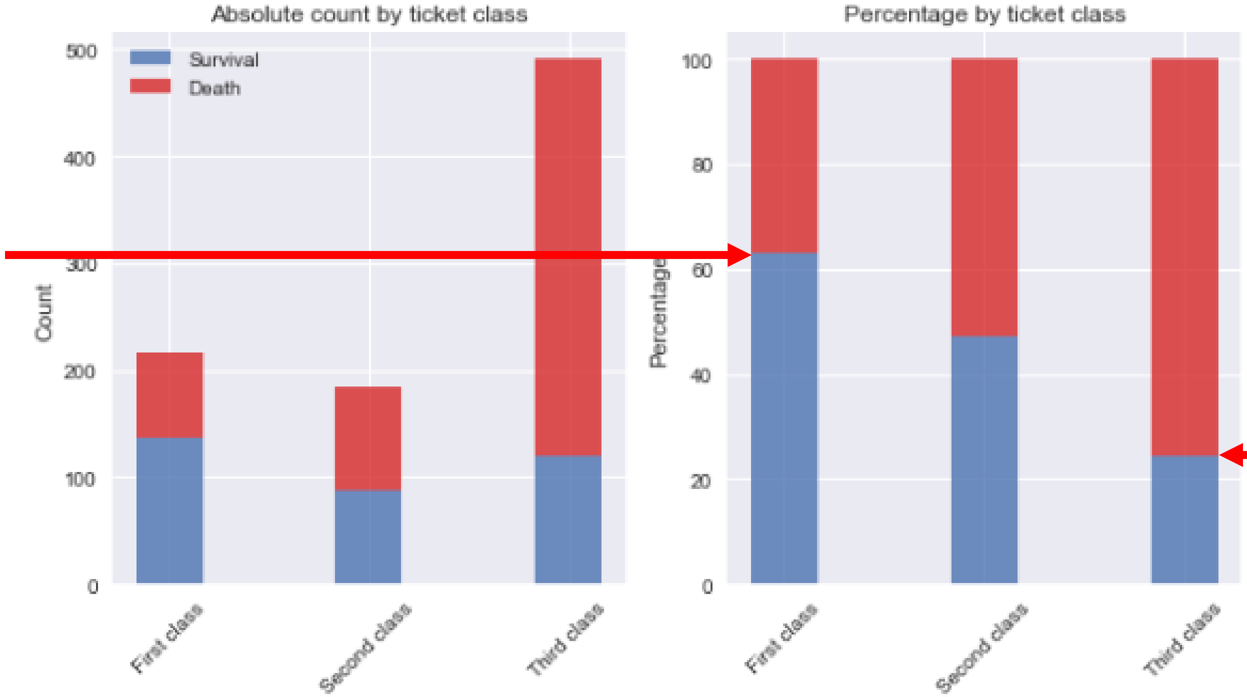
Should we delete the Passenger ID ??

Feature Construction

Passenger ID corresponds to the Ticket Class!

- Manually create a new feature “Ticket Class” which is derived from the “Passenger ID”.

First Class = 62.96% Survival Rate 😁



Third Class = 24.23% Survival Rate 😭

Data Encoding

Encode data in a representation the machine understands. Encoding should retain information.

Ordinal Data, i.e. ordered categories:

- Ordinal Encoding
- Cyclical Encoding

Nominal Data, i.e. unordered categories:

- Label Binarizing
- One-Hot Encoding
- Dummy Encoding

Text Data, i.e. unstructured raw text:

- Word Statistics
- Bag-of-Words
- TF-IDF
- Word Embeddings

Hot, Hotter, Hottest

Date and Time

Fruit Type

Race, Gender

Pros and Cons of Different Encoding Strategies?

Emails, Webpages, etc.

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum. Sed ut perspiciatis unde omnis iste natus error sit voluptatem accusantium doloremque laudantium, totam rem aperiam, eaque ipsa quae ab illo inventore veritatis et quasi architecto beatae vitae

Do we always need to encode our data?

Imputation

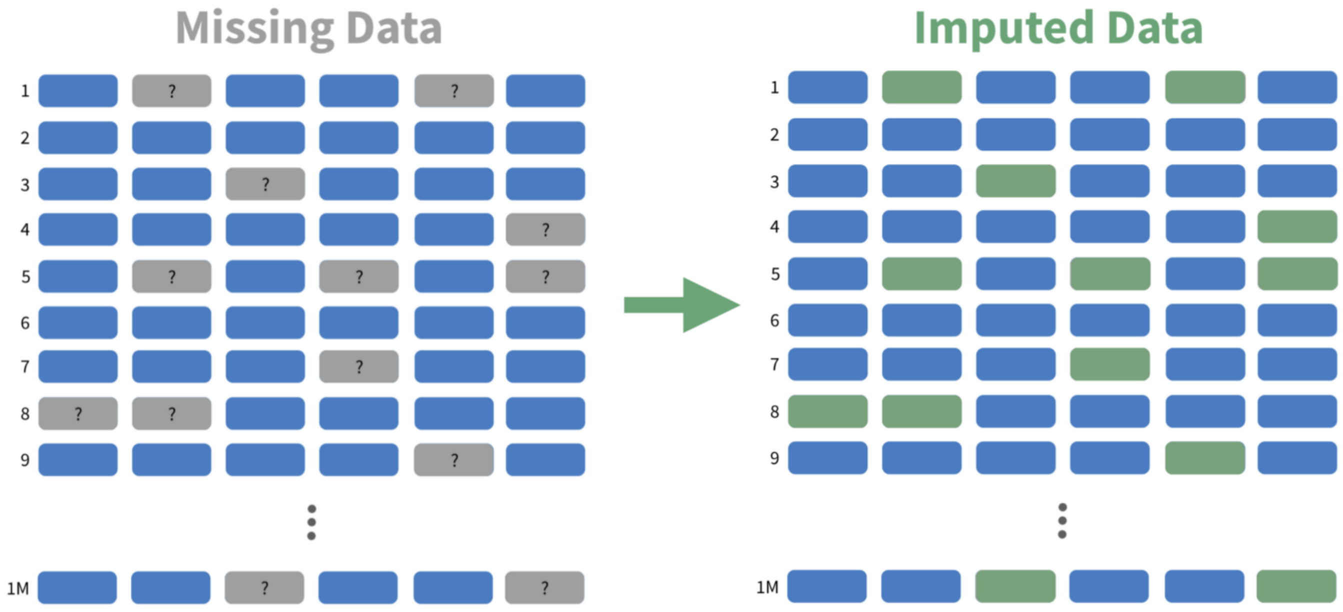
The process of **replacing missing data** with substituted values.

Common Imputation Strategies:

- Mean Imputation
- Mode Imputation
- Hot Deck Imputation
- Cold Deck Imputation
- Nearest Neighbour Imputation
- …

Imputation vs Removal vs Nothing?

- Imputation runtime concerns
- Instance missing multiple features
- Model can handle missing values



https://scikit-learn.org/stable/modules/impute.html
https://en.wikipedia.org/wiki/Imputation_(statistics)

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Machine Learning Modelling

Selecting a Machine Learning Model

Question: So many options … which machine learning model should be used?

Answer: It depends on your data and requirements.

For tabulated data (*i.e.* our kaggle competition) some suggestions:

- **Linear Models** – Logistic Regression, Elastic Net, GAMs, …
- **Tree Ensembles** – Random Forest, Gradient Boosting, XGBoost, …
- **Neural Networks** – Feed-Forward Neural Networks, TabNet, …

Side Note: For Computer Vision and Natural Language Processing:

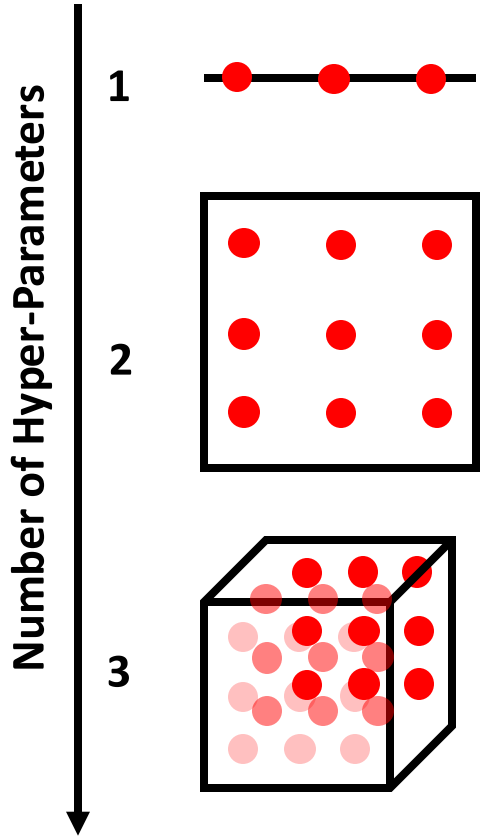
- **Neural Networks** - Convolutional Neural Networks and Transformers.

Things to consider when choosing a model:

- Training and inference runtime
- Time to implement algorithm/method
- Predictive performance of the model

Hyper-Parameter Optimization

Parameters which **controls the settings of the algorithm**. Not directly learned by the algorithm/model, e.g. k in k-nearest neighbour.



How to select the best hyper-parameters for your model?

1. Start with the default used by the library.
2. Learn about you chosen machine learning model.
3. Identify which hyper-parameters (1 or 2) are most important.
4. Grid Search or Random Search.

Practical Advice for Kaggle Competition:

Do better Hyper-parameter optimization techniques exist? **A: Yes.**
Do you have enough time and computational resources? **A: Probably not.**

Bagging, Boosting, and Stacking

Ensembling approaches for **combine multiple machine learning techniques into one** model in order to improve the performance.

Bagging: Models learn independently from each other in parallel and then combined by taking the average prediction across models.

Stacking: Models learn independently from each other in parallel and then combined by using a meta-model to output the final prediction.

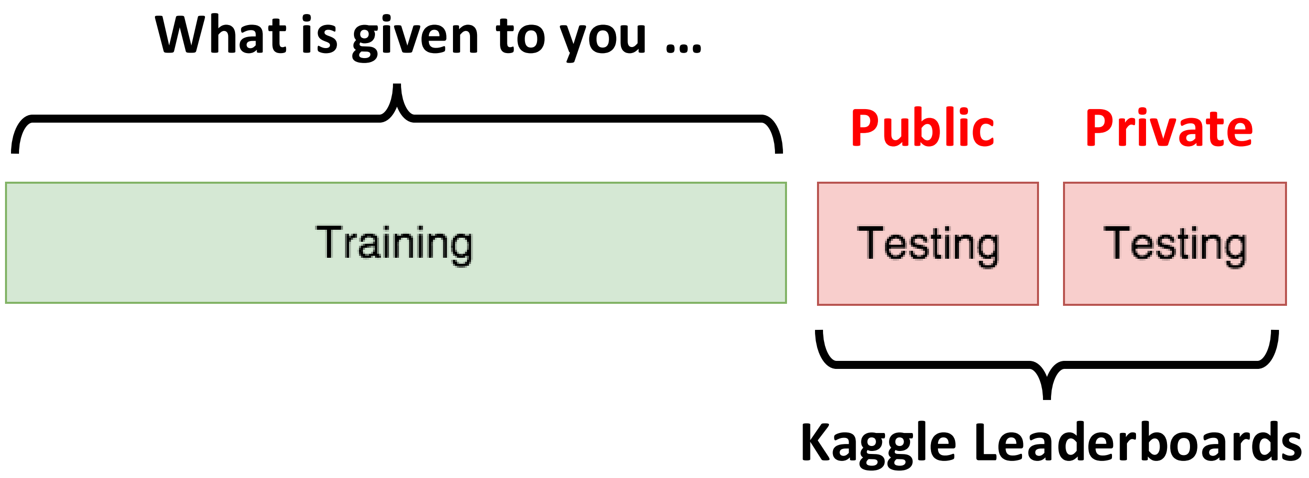
Boosting: Models learn sequentially in an adaptative way (a model depends on the previous ones) and combines them following a strategy.

https://towardsdatascience.com/ensemble-methods-bagging-boosting-and-stacking-c9214a10a205
https://scikit-learn.org/stable/modules/ensemble.html

Model Evaluation and Validation

Cross Validation

Techniques for **assessing how a machine learning model will generalize to new unseen data**. Mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will **perform in the real world**.



Cross Validation Techniques:

- Training-Testing Split
- Training-Validation-Testing Split
- k-Fold Cross-Validation

- Stratified Cross-validation
- Leave-k-Out Cross-Validation
- Leave-One-Out Cross-Validation
- Random Sub-Sampling Validation

Suggested Reading!

https://mlu-explain.github.io/train-test-validation/
https://en.wikipedia.org/wiki/Cross-validation_(statistics)

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Kaggle Competition Public Leaderboard

#	Team	Members	Score	Entries	Last	Code
1	HowOrdinawy		0.99691	6	1y	
2	Shaun C.		0.99485	18	1y	
3	Dave from Chorus		0.99205	10	1y	
4	Jeffffffffff		0.97470	6	1y	
5	New_ai		0.96411	28	1y	
6	PattttttttttttzRY		0.93676	5	1y	
7	Maxwell Grigson		0.84441	8	1y	
8	FlyingAlpaca		0.80250	5	1y	
9	GaoYuan		0.80176	12	1y	
10	happydemic		0.78794	9	1y	
11	MurpheyWu		0.78455	37	1y	
12	Globlax		0.78308	5	1y	

173	173	1,591
Teams	Competitors	Entries

Example of the top *public* submissions from last years Kaggle competition

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Kaggle Competition Private Leaderboard

#	△	Team	Members	Score	Entries	Last	Code
1	▲ 7	FlyingAlpaca		0.81030	5	1y	
2	▲ 7	GaoYuan		0.79840	12	1y	
3	▲ 7	happydemic		0.79098	9	1y	
4	▲ 3	Maxwell Grigson		0.78750	8	1y	
5	▲ 6	MurpheyWu		0.78439	37	1y	
6	▼ 4	Shaun C.		0.78386	18	1y	
7	▲ 6	eau		0.78113	14	1y	
8	▲ 6	DONDA		0.78045	9	1y	
9	▲ 3	Globlax		0.77113	5	1y	
10	▼ 7	Dave from Chorus		0.74803	10	1y	
11	▲ 4	Bayden		0.73053	13	1y	
12	▼ 11	HowOrdinawy		0.72348	6	1y	

Models which **overfitted the public leaderboard failed to generalize** their performance to the private leaderboard.

Largest Increase in Rank ▲ **32**

Largest Decrease in Rank ▼ **83**

Assignment Tips

Project File Structure

Suggested Project Structure:

- Separate the code logic from the data.
- Maintaining version control for the data

- **Project Root**
  - **Source Code**
    - main.py
    - analysis.py
    - preprocessing.py
    - model.py
  - **Data**
    - **Original Data**
    - **Cleaned Data**
    - ⋮ ⋮
    - **Final Data**
  - report.pdf

Source Code

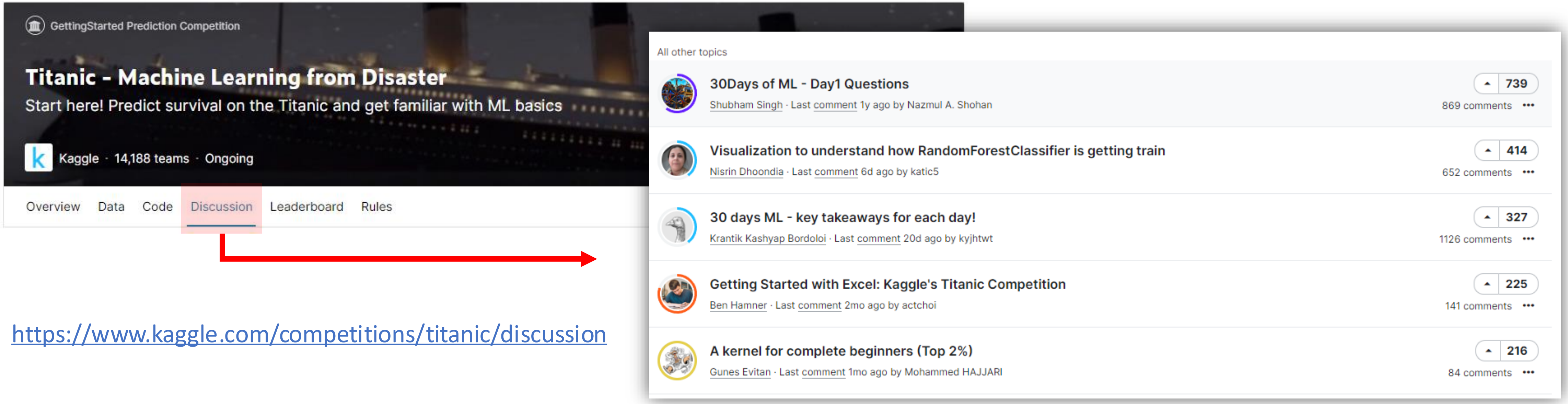
- Run code from main file, separate out the ML pipeline stages.

Data Version Control

- Don't need to run pre-processing pipeline every time can just load data.

Closing Remarks

1. The report is what is marked. **Ensure you document all the hard work you are doing**!
2. To do well in the competition you need to **do your own research**. Get creative.
3. **Discuss your approach** with your peers (but beware of plagiarism) and tutors.
4. Read the **discussion sections of past Kaggle competitions**.



https://www.kaggle.com/competitions/titanic/discussion