Machine Learning Using Python

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Workshop Objectives

- Collect data from a variety of sources
- Explore large data sets
- Clean and "munge" the data to prepare it for analysis
- Apply machine learning algorithms to gain insight from the data
- Visualize the results of your analysis
- Build your own library and Python scripts

Self Introduction

Self Introduction

- Name
- Background
- What do you want to gain out of this course?
- Experience in programming and data analytics?

Day 1 - Developing the Fundamentals

- Introduction to Machine Learning (AM)
  - What is machine learning?
  - Installation and update of tools
- Exploring and using Data Sets (PM)
  - Learn the steps to pre-process a data set and prepare it for machine learning algorithms
  - Introduction to machine learning algorithms – linear & logistic regression

Day 2 - Diving into Machine Learning

- Supervised vs Unsupervised Learning (AM)
  - Decision trees, random forests, K-nearest neighbors
  - K-means, hierarchical clustering
- Model Evaluation (PM)
  - Feature engineering and model selection
  - Model evaluation metrics
  - Overfitting and bias-variance trade-off
  - Cross validation

Introduction to Machine Learning

Background and Context

1. Data is increasingly cheap and ubiquitous

2. New technologies are emerging to organize and make sense of this avalanche of data

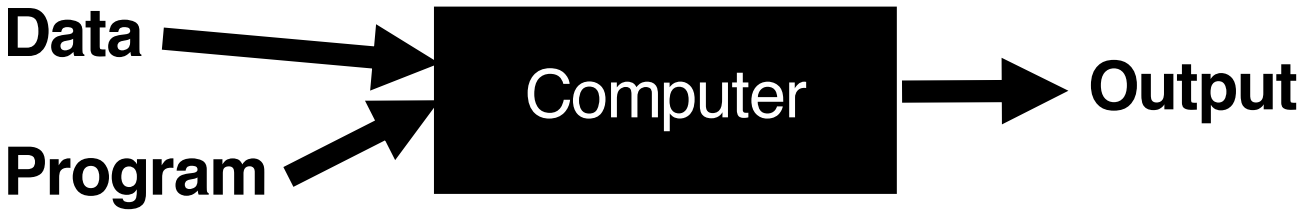
3. Organizations need to harness internal and external data effectively to attract and retain their customers

What is Data Science?

- A set of tools and techniques for data
- Interdisciplinary problem-solving
- Application of scientific techniques to practical problems
- The scientific approach to knowledge extraction from data

What is Machine Learning?

Traditional Programming



Machine Learning

Machine learning is a field of computer science that often uses statistical techniques to give computers the ability to “learn” (i.e., progressively improve performance on a specific task) with data, without being explicitly programmed

Who uses Machine Learning?

NETFLIX

amazon.com

Google

Grab

FiveThirtyEight

LAZADA
Effortless Shopping

DBS

GOVTECH
SINGAPORE

Singapore Examples – Is this Machine Learning?

datagovsg Follow
Official Medium account for https://data.gov.sg, Singapore's open data portal.
Dec 1, 2016 · 8 min read

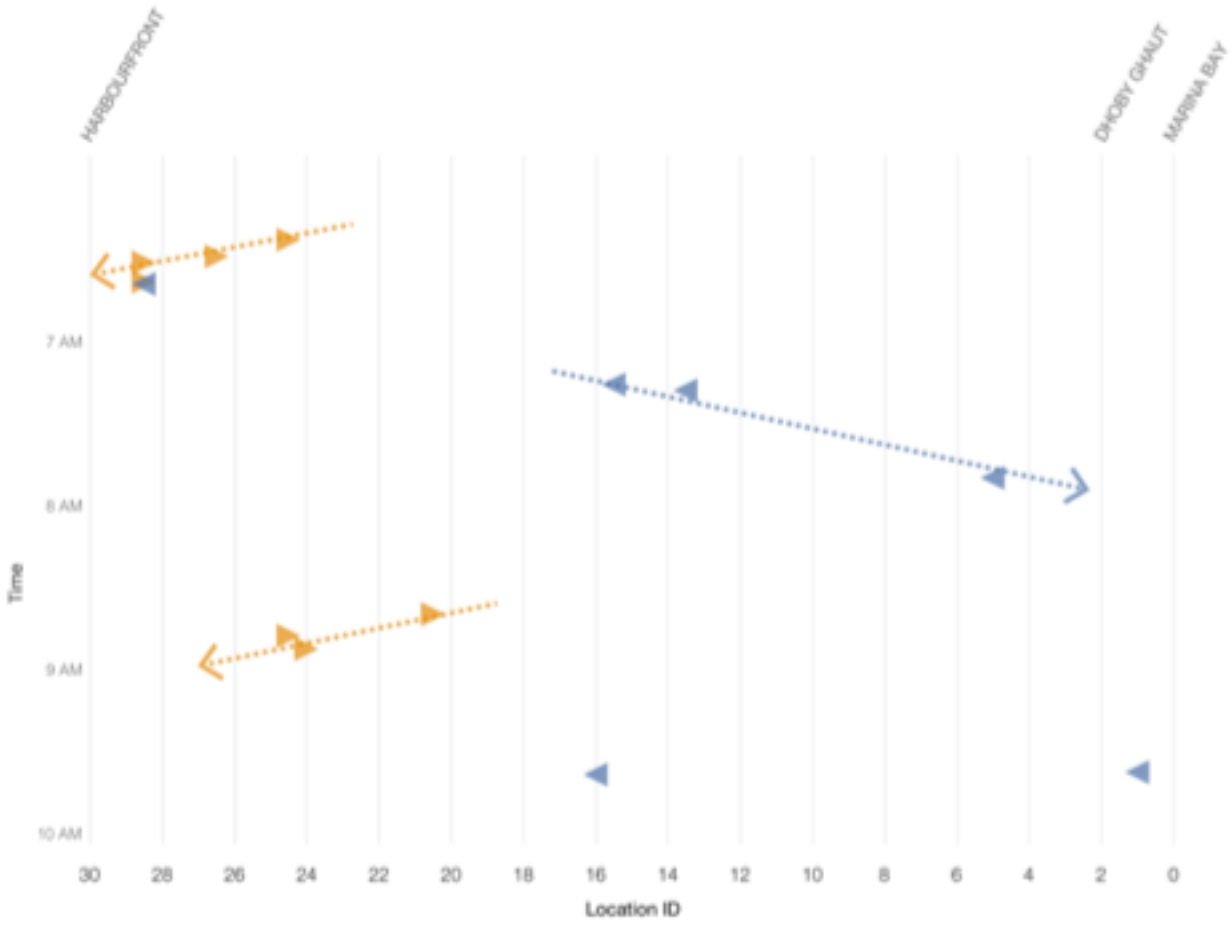
How the Circle Line rogue train was caught with data

Text: Daniel Sim | Analysis: Lee Shangqian, Daniel Sim & Clarence Ng

Singapore's MRT Circle Line was hit by a spate of mysterious disruptions in recent months, causing much confusion and distress to thousands of commuters.

DIGITALGOV 28 December 2016

Rogue Train: A Big Data Story



https://blog.data.gov.sg/how-we-caught-the-circle-line-rogue-train-with-data-79405c86ab6a

Singapore Examples – Is this Machine Learning?

Yellow taxis have fewer accidents than blue ones, says study

Researchers from NUS and the Chinese University of Hong Kong say that yellow taxis are more noticeable than blue taxis in both daylight and under street lighting. PHOTO: BLOOMBERG NEWS

PUBLISHED MAR 8, 2017, 5:00 AM SGT | UPDATED MAR 8, 2017, 11:01 AM

Tay Hong Yi

The next time you hail a taxi, take note of its colour, for it might mean a safer ride.

Researchers at the National University of Singapore (NUS) found that taxis painted yellow, a colour that stands out, were involved in significantly fewer traffic accidents than taxis painted blue.

Their results were based on analysing three years' worth of detailed taxi, driver and accident data from a large fleet of over 4,000 yellow taxis and 12,500 blue taxis locally.

Yellow taxis have fewer accidents than blue taxis because yellow is more visible than blue

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Edited by George A. Akerlof, University of California, Berkeley, CA, and approved January 31, 2017 (received for review August 3, 2016)

Is there a link between the color of a taxi and how many accidents it has? An analysis of 36 mo of detailed taxi, driver, and accident data (comprising millions of data points) from the largest taxi company in Singapore suggests that there is an explicit link. Yellow taxis had 6.1 fewer accidents per 1,000 taxis per month than blue taxis, a 9% reduction in accident probability. We rule out driver difference as an explanatory variable and empirically show that because yellow taxis are more noticeable than blue taxis—especially when in front of another vehicle, and in street lighting—other drivers can better avoid hitting them, directly reducing the accident rate. This finding can play a significant role when choosing colors for public transportation and may save lives as well as millions of dollars.

car color | road safety | data science | transportation science | sensory perception

Accidents involving public transport are common and cause significant economic losses as well as loss of human life. Applying statistical analysis to a unique and comprehensive dataset we establish that a change in color can avert a significant number of taxi accidents, leading to a reduction in economic losses. Specifically, analysis of a complete set of accident records from the largest taxi operator in Singapore, which uses yellow and blue taxis, shows that yellow is safer than blue because yellow is more noticeable, with the result that potential accidents are avoided by other drivers' timely responses.

Yellow has been a popular color for taxis since 1907, when the Chicago Yellow Cab Company chose the color based on a survey conducted at the University of Chicago. The survey showed that yellow was the most noticeable color, which would make it easy for potential passengers to spot a yellow taxi in the sea of mass-demographic characteristics. These two datasets include millions of observations on the company's drivers and taxis, and accidents involving these taxis. The data from both datasets have been anonymized and are available in Datasets S1–S6.

The company uses yellow or blue for all its regular taxis (approximate colors are shown in Fig. 1).[1] The colors are the remnants of a 2002 merger that took place between two taxi companies, one of which used yellow and the other, blue. The company owns ~16,700 taxis in a ratio of one yellow to three blue (1y:3b), which translates to 4,175 yellow taxis and 12,525 blue ones. These account for 60% of the ~27,800 taxis in Singapore.[2]

To control for the difference in the number of taxis used by the company (1y:3b), we calculated a normalized accident rate using the average number of accidents that occurred per 1,000 taxis

Significance

This paper examines the phenomenon that yellow taxis have fewer accidents than blue taxis. Statistical analysis of a unique and comprehensive dataset suggests that the higher visibility of the color yellow makes it easier for other drivers to avoid getting into accidents with yellow taxis, leading to a lower accident rate. This suggests that color visibility should play a major role in determining the colors used for public transport vehicles.

Author contributions: T.-H.H. and J.K.C. designed research; T.-H.H. and J.K.C. performed research; T.-H.H., J.K.C., and X.X. contributed new reagents/analytic tools; T.-H.H., J.K.C., and X.X. analyzed data; and T.-H.H., J.K.C., and X.X. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

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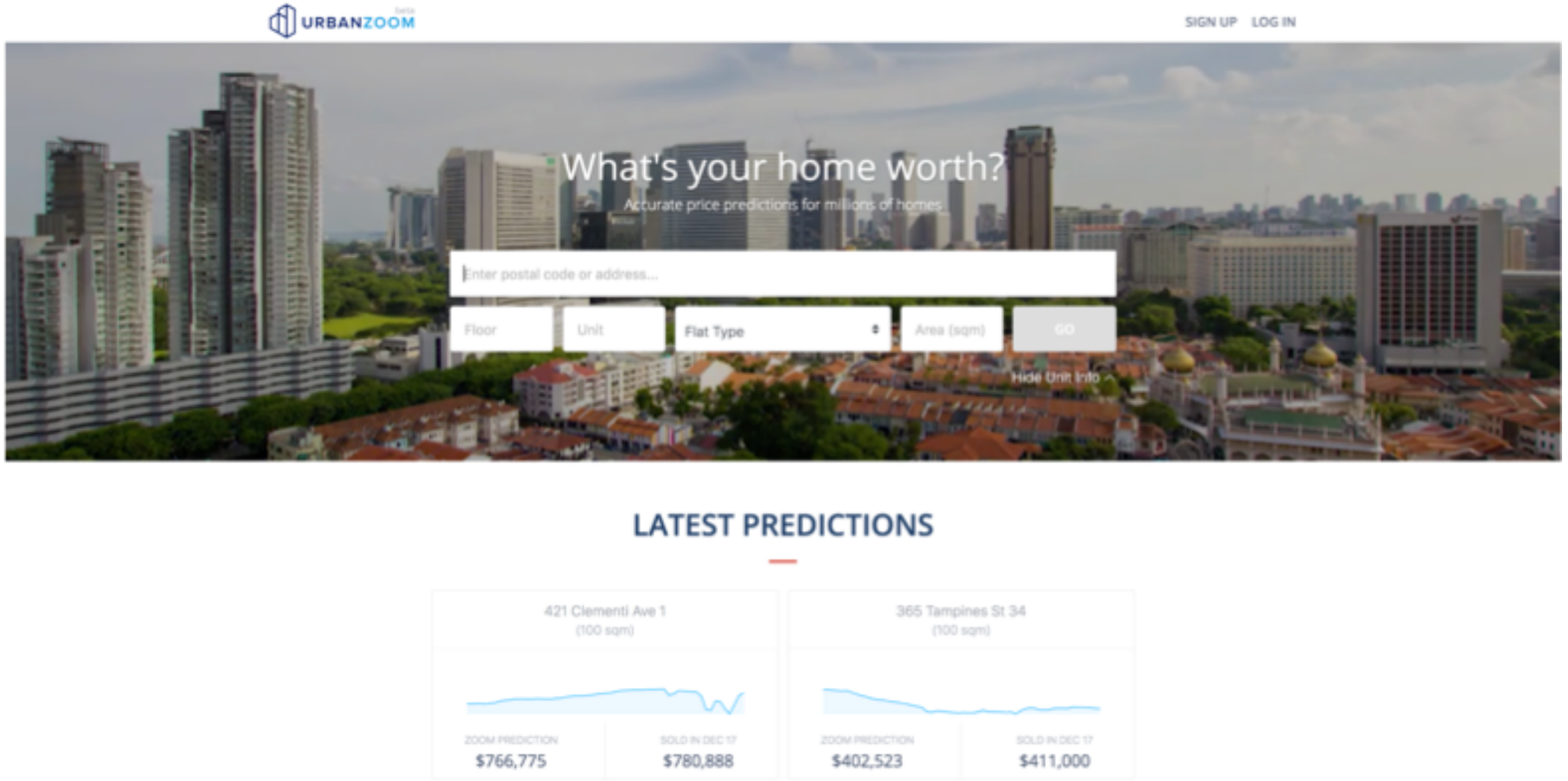
Singapore Examples – Is this Machine Learning?



Common Questions asked in Machine Learning

How much? How many?

- What will the stock price of Microsoft be next week?
- What will my fourth quarter sales be?
- How many kilowatts of electricity will be demanded between 7-8pm?
- How many new Twitter followers will I get next week?

Regression

Predict a continuous outcome

- Linear Regression
- K-Nearest Neighbors
- Regression Trees

Common Questions asked in Machine Learning

Is this A, B, or C?

- Is this a fraudulent transaction?
- Is this an image of a man, a cat, or a dog?
- Will this customer click on the advertisement?
- Is the sentiment of the review positive or negative?

Classification

Predict a discrete outcome

- Logistic Regression
- K-Nearest Neighbors
- Classification Trees

Common Questions asked in Machine Learning

How is this data organized?

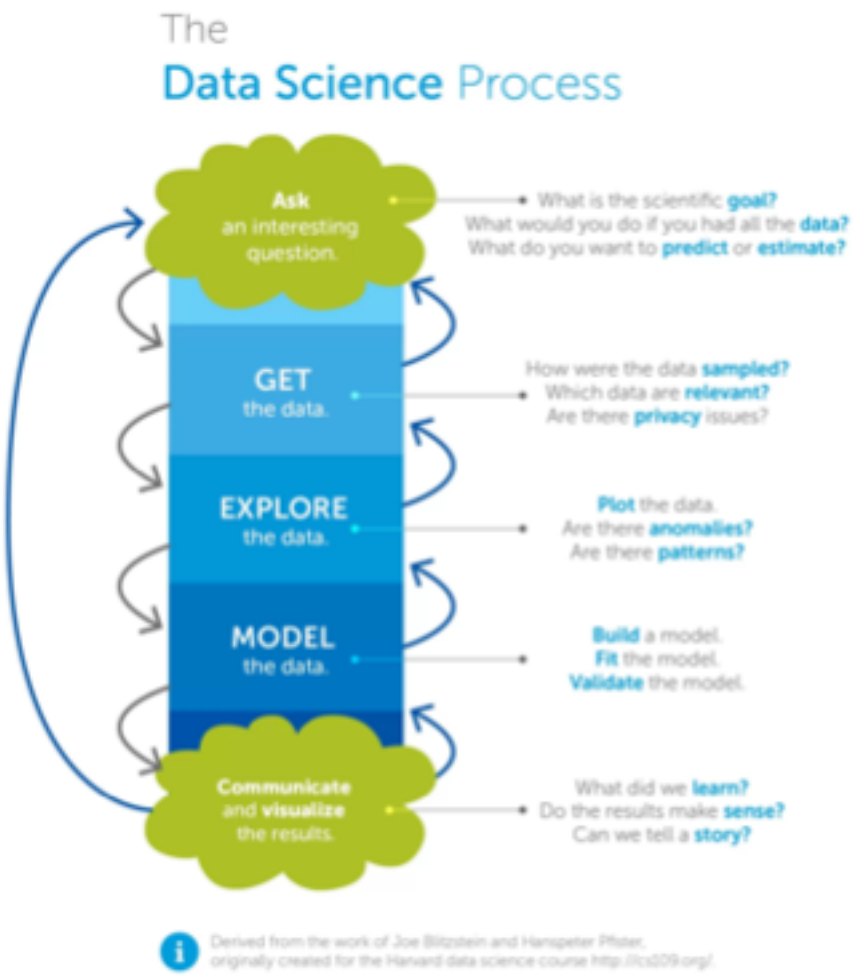
- What are the different types of coffee drinkers?
- Which viewers like the same kind of movies?
- Are there common clusters of cable channels that customers tend to purchase together?
- What is a natural way to break these documents into five topics?

Clustering

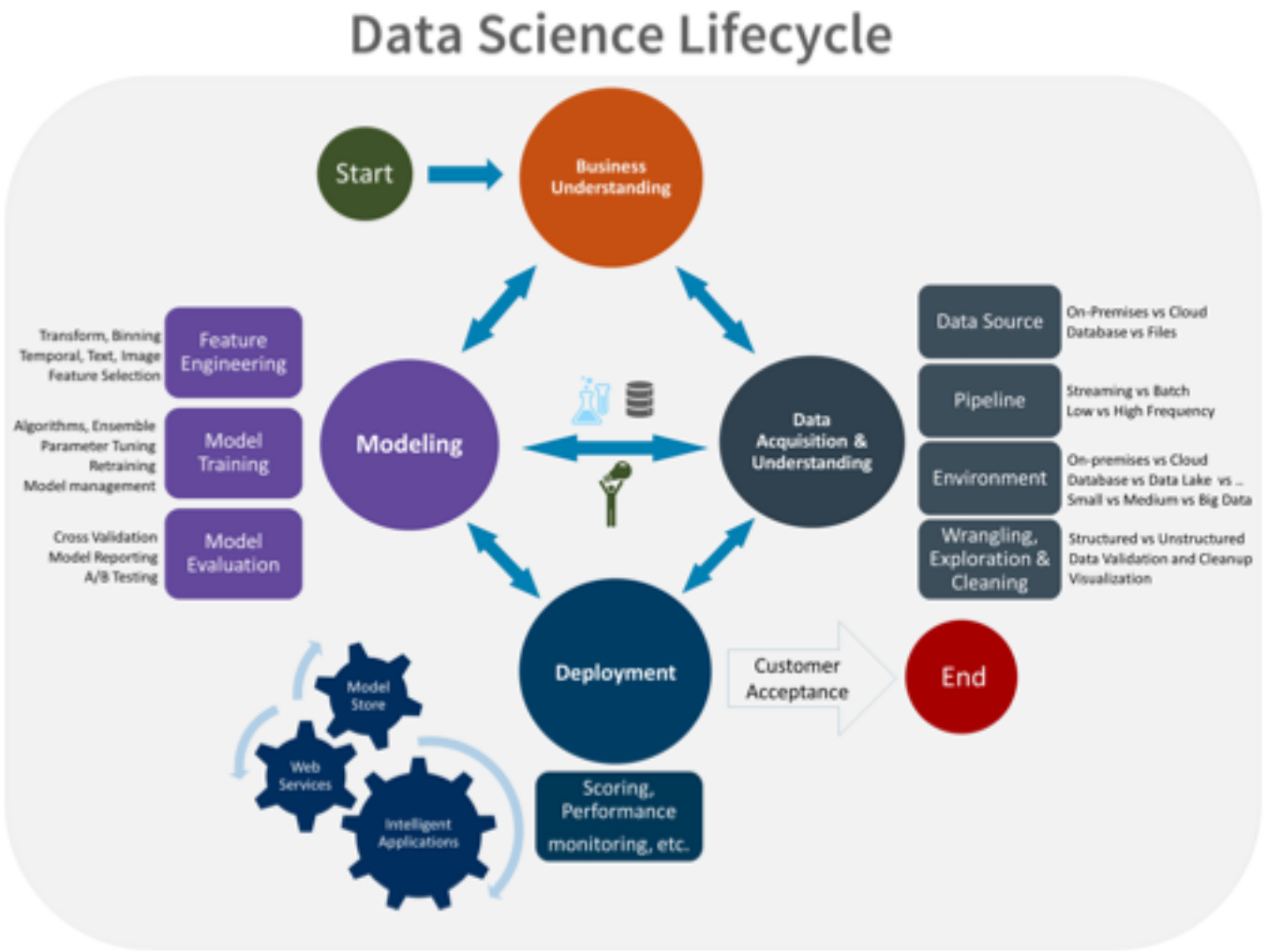
Segment data into different groups

- K-Means Clustering
- Hierarchical Clustering

Data Science / Machine Learning Process



Data Science Process Lifecycle



Ask an Interesting (Impactful) Question

- Begin by identifying the objectives and desired outcomes of the analysis
- Typical scenarios:
  - Given dataset(s) and tasked to explore and uncover insights
  - Specific business problem and need to source the relevant data

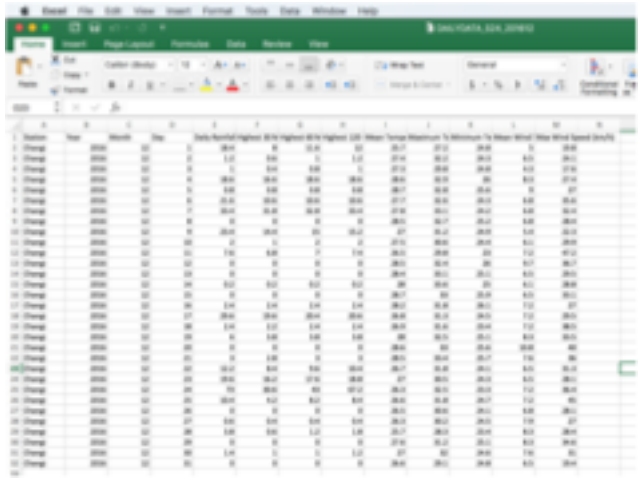
Example Problem Statement: What will the expected resale value of my HDB flat be in 10 years time?

Get the Data

- Internal data – spreadsheets, csv files, databases, system logs
- External data – csv files, API requests, web scraping

Get the Data

- Structured data – well formatted, data schema defined, easy to parse
- Unstructured data – may require additional processing or programming tools to extract relevant metadata e.g. sentiments, word count, entities
- Semi-structured data – may require use of regex or programming logic to extract relevant fields e.g. logs, JSON, XML



Structured

ORAL ANSWERS TO QUESTIONS

FEATURES FOR MERGED SKILLSFUTURE AND JOBS BANK PORTALS

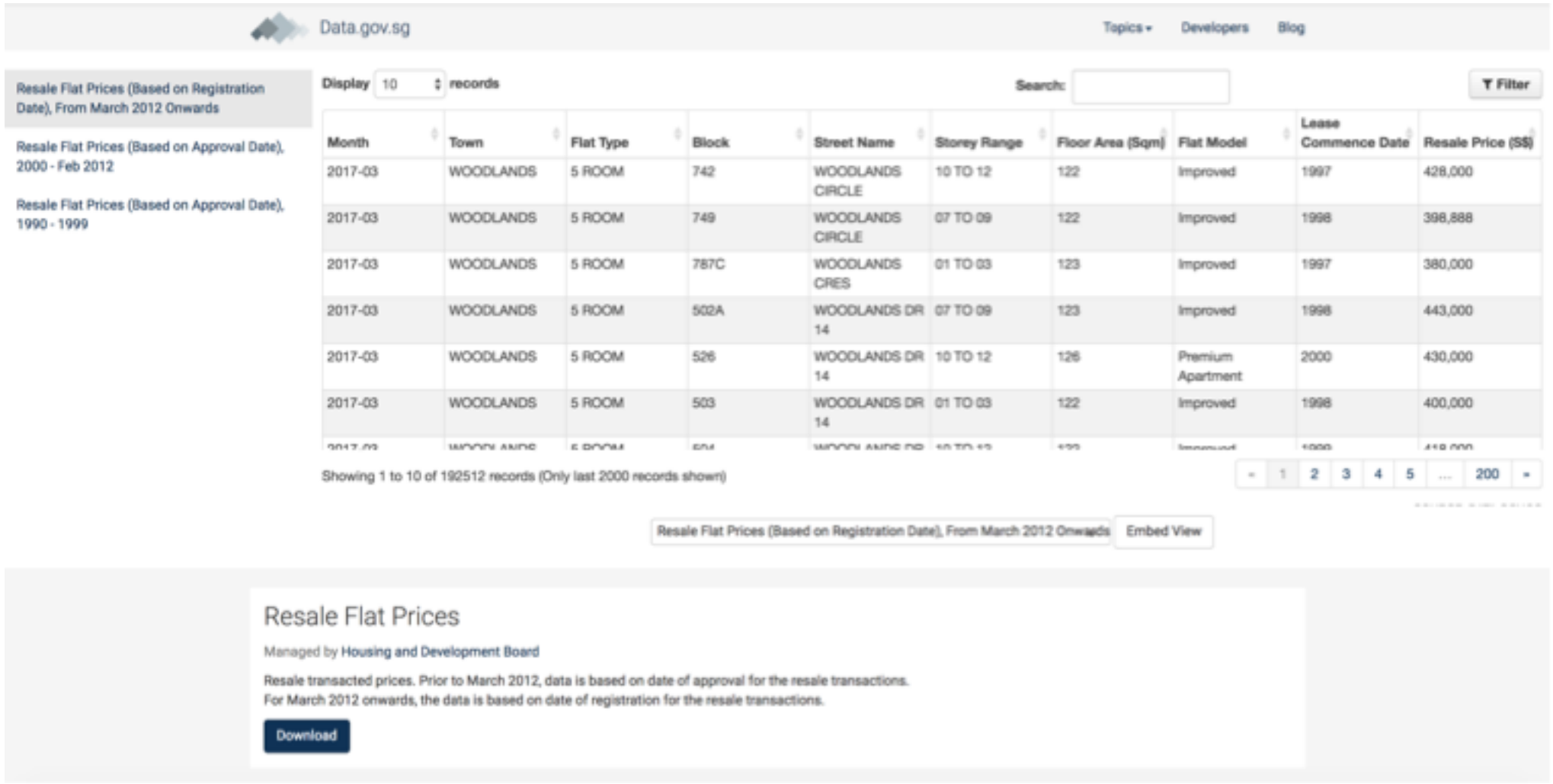
1 **Ms Sun Xueling** asked the Minister for Education (Higher Education and Skills) (a) whether the merger of the SkillsFuture and Jobs Bank portals will incorporate a review function for training providers to ensure outcome-based training provisions; (b) whether the merged portal can include internship opportunities for young Singaporeans; (c) whether the merged portal can include personality assessments that gauge the fit of the user to jobs as opposed to just skills; and (d) whether jobs listed in the Jobs Bank are regularly updated to ensure relevance.

The Parliamentary Secretary to the Ministers for Education (Assoc Prof Dr Muhammad Faishal Ibrahim) (for the Minister for Education (Higher Education and Skills)) : Madam, the Individual Learning Portfolio (ILP) is designed to be a one-stop online portal which empowers individuals to make informed learning and career choices. There will be platforms for individuals to review and provide feedback on the training programmes available on the ILP, and information on training outcomes will be published on the portal.

Unstructured

Semi-structured

Get the Data


Data.gov.sg
Topics
Developers
Blog
Resale Flat Prices (Based on Registration Date), From March 2012 Onwards
Resale Flat Prices (Based on Approval Date), 2000 - Feb 2012
Resale Flat Prices (Based on Approval Date), 1990 - 1999
Display 10 records
Search:
Filter
Month | Town | Flat Type | Block | Street Name | Storey Range | Floor Area (Sqm) | Flat Model | Lease Commence Date | Resale Price (S$)
2017-03 | WOODLANDS | 5 ROOM | 742 | WOODLANDS CIRCLE | 10 TO 12 | 122 | Improved | 1997 | 428,000
2017-03 | WOODLANDS | 5 ROOM | 749 | WOODLANDS CIRCLE | 07 TO 09 | 122 | Improved | 1998 | 398,888
2017-03 | WOODLANDS | 5 ROOM | 787C | WOODLANDS CRES | 01 TO 03 | 123 | Improved | 1997 | 380,000
2017-03 | WOODLANDS | 5 ROOM | 502A | WOODLANDS DR 14 | 07 TO 09 | 123 | Improved | 1998 | 443,000
2017-03 | WOODLANDS | 5 ROOM | 526 | WOODLANDS DR 14 | 10 TO 12 | 126 | Premium Apartment | 2000 | 430,000
2017-03 | WOODLANDS | 5 ROOM | 503 | WOODLANDS DR 14 | 01 TO 03 | 122 | Improved | 1998 | 400,000
Showing 1 to 10 of 192512 records (Only last 2000 records shown)
« 1 2 3 4 5 ... 200 »
Resale Flat Prices (Based on Registration Date), From March 2012 Onwards
Embed View
Resale Flat Prices
Managed by Housing and Development Board
Resale transacted prices. Prior to March 2012, data is based on date of approval for the resale transactions.
For March 2012 onwards, the data is based on date of registration for the resale transactions.
Download

Explore the Data

- Review the data dictionary, understand what columns are present
- Check for missing values, data quality issues, outliers and anomalies

```
# Metadata for Resale Flat Prices
---
Identifier: '7a339d20-3c57-4b11-a695-9348adfd7614'
Name: 'resale-flat-prices'
Title: 'Resale Flat Prices'
Description:
  - 'Resale transacted prices.'
  - 'Prior to March 2012, data is based on date of approval for the resale transactions.'
  - 'For March 2012 onwards, the data is based on date of registration for the resale
    transactions.'
Topics:
  - 'Infrastructure'
Keywords:
  - 'Cost of Living'
  - 'HDB'
  - 'Housing'
  - 'Property'
  - 'Public Housing'
  - 'Resale Flats'
Publisher:
  Name: 'Housing and Development Board'
  Admin 1:
    Name: 'Michelle Tay'
    Department: 'CDG'
    Email: 'Michelle_MB_TAY@hdb.gov.sg'
Sources:
  - 'Housing and Development Board'
License: 'https://data.gov.sg/open-data-licence'
Frequency: 'Monthly'
Coverage: '1990-01-01 to 2017-04-30'
Last Updated: '2017-05-15T07:03:31.090642'
Resources:
  -
    Identifier: '83b2fc37-ce8c-4df4-968b-370fd818138b'
    Title: 'Resale Flat Prices (Based on Registration Date), From March 2012 Onwards'
    Url: 'https://storage.data.gov.sg/resale-flat-prices/resources/resale-flat-prices-based-on-regis
    Format: 'CSV'
    Coverage: '2012-03-01 to 2017-04-30'
    Last Updated: '2017-05-15T07:03:30.565947'
    Schema:
      -
        Name: 'month'
        Title: 'Month'
        Type: 'datetime'
        Sub Type: 'month'
        Format: 'YYYY-MM'
```

```
resale_prices.head()
```

	month	town	flat_type	block	street_name	storey_range	floor_area_sqm	flat_model	lease_commence_date	remaining_lease	resale_price
0	2015-01	ANG MO KIO	3 ROOM	174	ANG MO KIO AVE 4	07 TO 09	60.0	Improved	1986	70	255000.0
1	2015-01	ANG MO KIO	3 ROOM	541	ANG MO KIO AVE 10	01 TO 03	68.0	New Generation	1981	65	275000.0
2	2015-01	ANG MO KIO	3 ROOM	163	ANG MO KIO AVE 4	01 TO 03	69.0	New Generation	1980	64	285000.0
3	2015-01	ANG MO KIO	3 ROOM	446	ANG MO KIO AVE 10	01 TO 03	68.0	New Generation	1979	63	290000.0
4	2015-01	ANG MO KIO	3 ROOM	557	ANG MO KIO AVE 10	07 TO 09	68.0	New Generation	1980	64	290000.0

```
resale_prices.isnull().values.any()
```

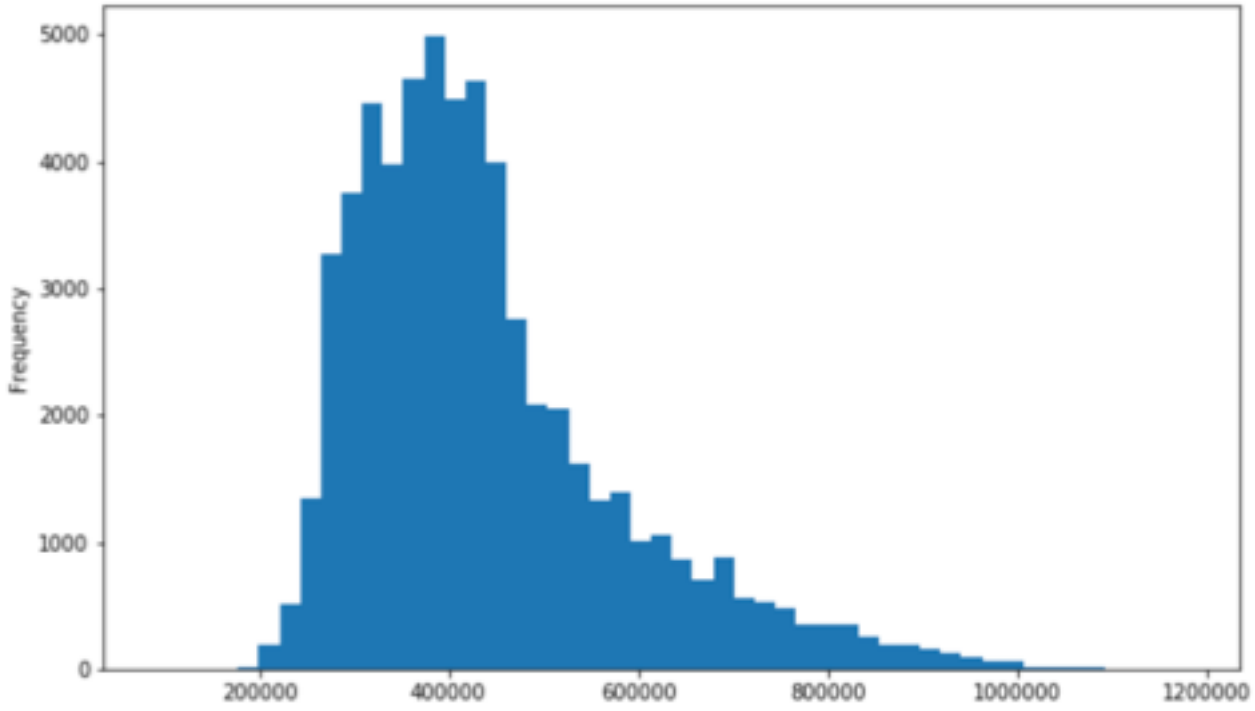
```
False
```

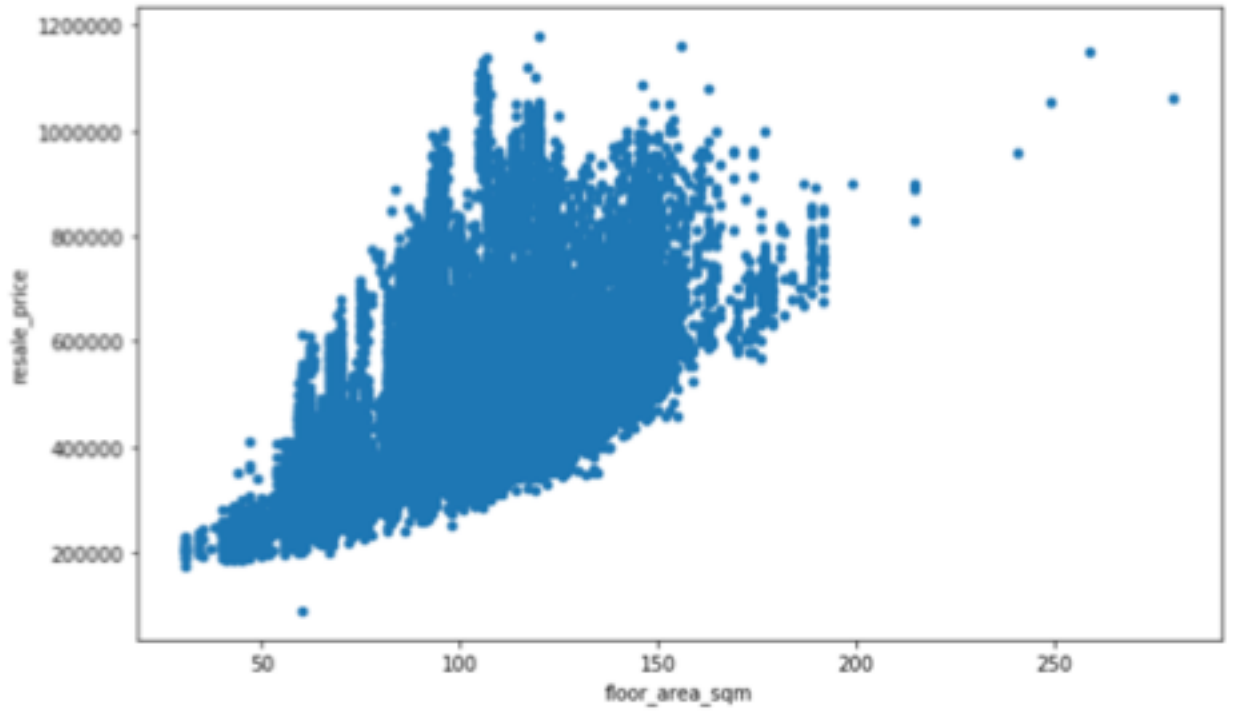
```
resale_prices.describe()
```

	floor_area_sqm	lease_commence_date	remaining_lease	resale_price
count	59809.000000	59809.000000	59809.000000	5.980900e+04
mean	97.319194	1991.607200	74.017890	4.394339e+05
std	24.166368	11.283492	11.274598	1.415803e+05
min	31.000000	1966.000000	47.000000	9.050000e+04
25%	75.000000	1984.000000	66.000000	3.400000e+05
50%	96.000000	1989.000000	72.000000	4.100000e+05
75%	111.000000	2001.000000	83.000000	5.000000e+05
max	280.000000	2015.000000	97.000000	1.180000e+06

Explore the Data

- Plot and visualize the data to understand distributions, trends and patterns





Model the Data

- Parse data into formats that are usable by the machine learning algorithm
- Create dummies (one hot encoding) for categorical values
- Perform feature engineering on the data

```
resale_prices = resale_prices.rename(columns={'month': 'year-month'})
resale_prices['year'] = resale_prices['year-month'].apply(lambda x: int(x.split("-")[0]))
resale_prices['month'] = resale_prices['year-month'].apply(lambda x: int(x.split("-")[1]))
resale_prices['lower_storey_range'] = resale_prices['storey_range'].apply(lambda x: int(x.split()[0]))
resale_prices['upper_storey_range'] = resale_prices['storey_range'].apply(lambda x: int(x.split()[2]))
```

```
df_flat_type = pd.get_dummies(resale_prices['flat_type'])
resale_prices = pd.concat([resale_prices, df_flat_type], axis=1)
```

Model the Data

- Predicting a continuous variable -> regression model
- Target variable -> resale_price
- Iteratively add, remove, or modify input variables, validate errors

```
from sklearn import linear_model
from sklearn.metrics import mean_squared_error
```

```
factors = ["floor_area_sqm", "upper_storey_range", "remaining_lease", "1 ROOM", "2 ROOM", "3 ROOM",
                        "4 ROOM", "5 ROOM", "EXECUTIVE", "MULTI-GENERATION"]
```

```
reg = linear_model.LinearRegression()
reg.fit(resale_train[factors], resale_train["resale_price"])
```

```
train_rmse = mean_squared_error(resale_train["resale_price"],
                                reg.predict(resale_train[factors]))**0.5
test_rmse = mean_squared_error(resale_test["resale_price"],
                               reg.predict(resale_test[factors]))**0.5
print("Train RMSE: {}".format(train_rmse))
print("Test RMSE: {}".format(test_rmse))
```

```
Train RMSE: 91428.75090177791
Test RMSE: 102976.87624708698
```

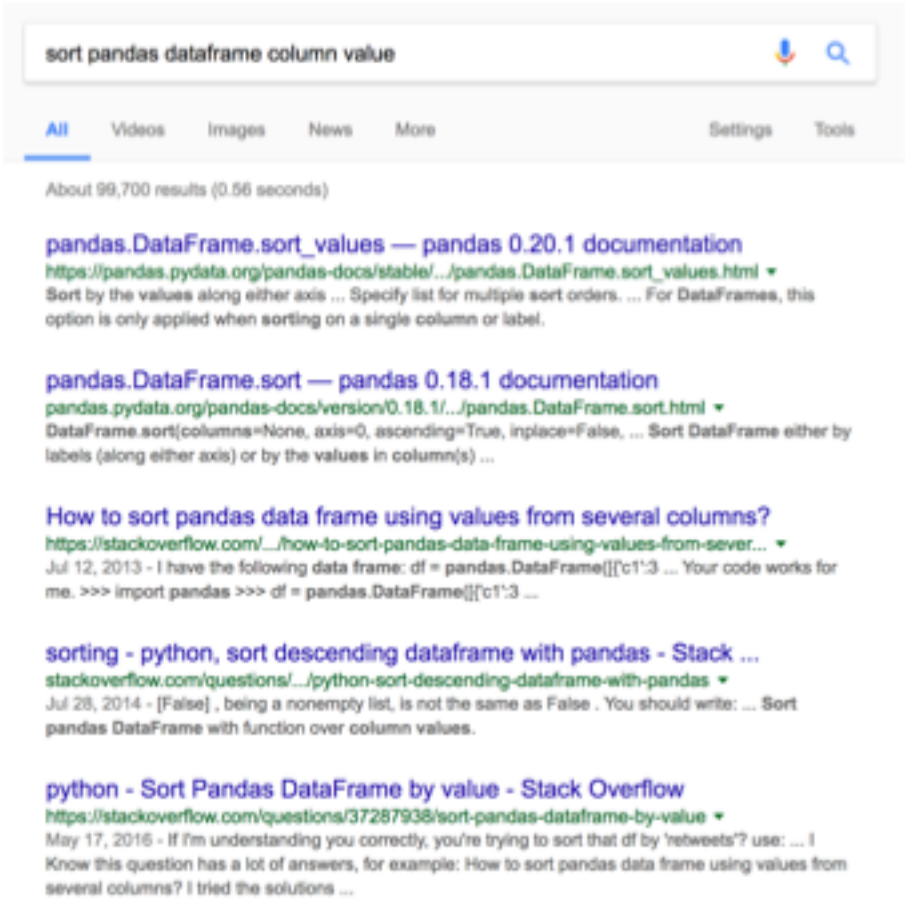
Communicate the Results

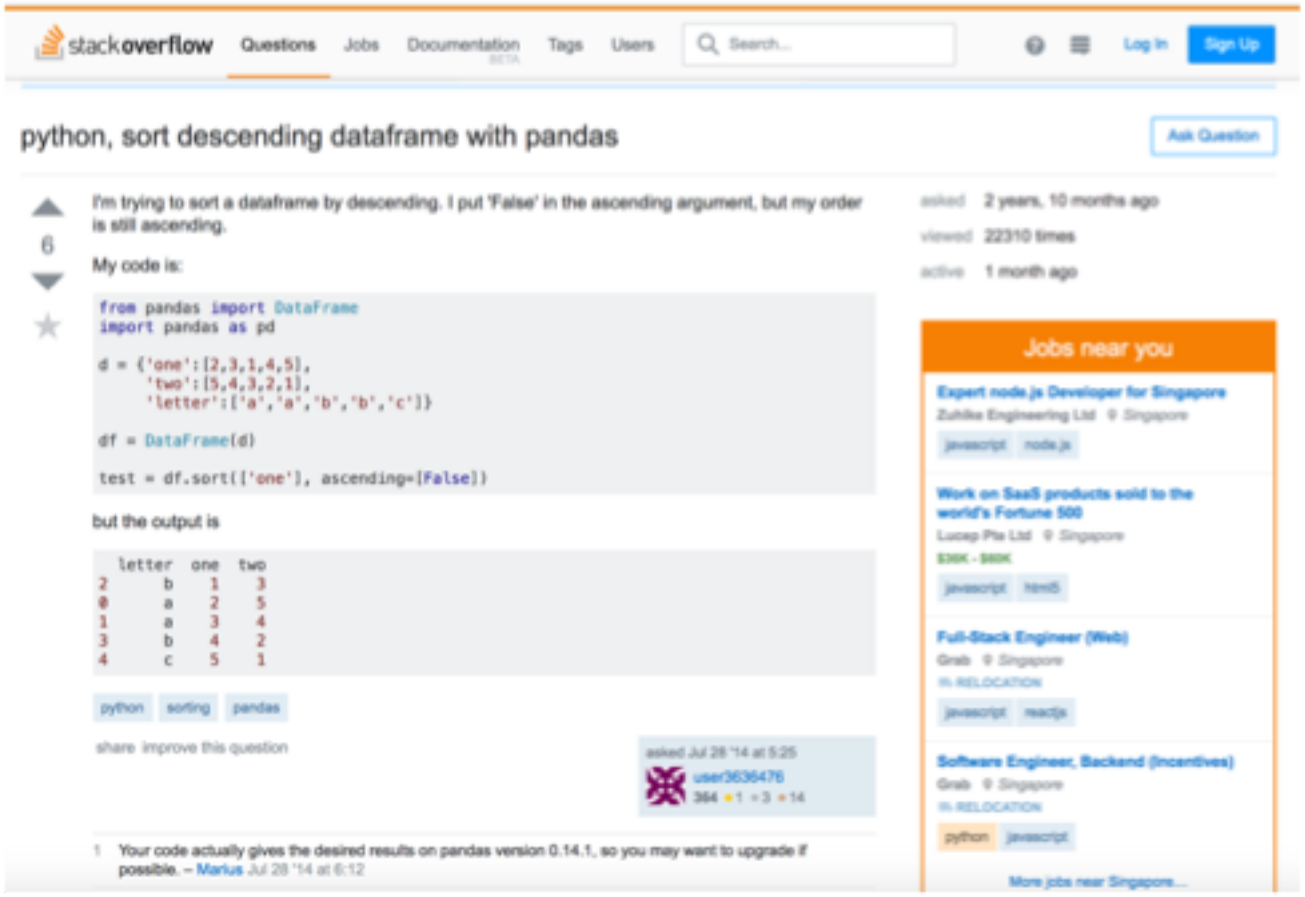
- We have developed a linear regression model to predict the resale price of a HDB flat based on factors including floor_area_sqm, remaining_lease, and flat_type.
- The training root mean squared error of the model is $90k and the testing root mean squared error is $100k
- The predicted flat price increases by $2.5k per sqm and $318 per year of remaining lease

Environment Setup

Getting Help

Google and Stack Overflow are your friend





Getting Help

Check the documentation

Getting Help

Review the error logs

```
resale_prices = pd.read_cs('data/resale-flat-prices-based-on-registration-date-from-march-2012-onwards.csv')
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-19-de8346ce4883> in <module>()
----> 1 resale_prices = pd.read_cs('data/resale-flat-prices-based-on-registration-date-from-march-2012-onwards.csv')

AttributeError: 'module' object has no attribute 'read_cs'
```

```
resale_price.head()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-21-e451aa5364ef> in <module>()
----> 1 resale_price.head()

NameError: name 'resale_price' is not defined
```

Getting Help

- If you can’t resolve the problem yourself within half an hour, reach out for assistance via our class Slack channel or on Stack Overflow
- Provide details about the steps you have taken, code you are running and errors to facilitate troubleshooting

Development Environment Setup

- Brief intro of tools
- Environment setup
  - Create a Github account https://github.com/
  - Install Github Desktop https://desktop.github.com/
  - Install Anaconda and Python 3.6 https://www.anaconda.com/download/
  - Clone the course Repo https://github.com/thufirtan/machinelearningpython
- Jupyter Notebook test

Exploring and using Datasets

Getting and Importing Data

- Determine if we have the “right” dataset for our problem
- Questions to ask about the data:
  - What type of data is it? Cross-sectional or longitudinal?
  - How was the data collected?
  - Is there much missing data?
  - Was the data collection instrument validated and reliable?
  - Is the dataset aggregated?
  - Do we need pre-aggregated data?

Understanding Your Data

- You need to understand what you are working with
- To better understand your data
  - Create or review the data dictionary
  - Perform exploratory surface analysis
  - Describe data structure and information being collected
  - Explore variables and data types

Data Dictionaries and Documentation

- Data dictionaries help judge the quality of the data
- They also help understand how it's coded
  - Does gender = 1 mean female or male?
  - Is the currency dollars or euros?
- Data dictionaries help identify any requirements, assumptions, and constraints of the data
- They make it easier to share data

Data Dictionary Examples

```
VARIABLE DESCRIPTIONS:
survival        Survival
                (0 = No; 1 = Yes)
pclass          Passenger Class
                (1 = 1st; 2 = 2nd; 3 = 3rd)
name            Name
sex             Sex
age             Age
sibsp           Number of Siblings/Spouses Aboard
parch           Number of Parents/Children Aboard
ticket          Ticket Number
fare            Passenger Fare
cabin           Cabin
embarked        Port of Embarkation
                (C = Cherbourg; Q = Queenstown; S = Southampton)

SPECIAL NOTES:
Pclass is a proxy for socio-economic status (SES)
 1st ~ Upper; 2nd ~ Middle; 3rd ~ Lower

Age is in Years; Fractional if Age less than One (1)
 If the Age is Estimated, it is in the form xx.5

With respect to the family relation variables (i.e. sibsp and parch)
some relations were ignored.  The following are the definitions used
for sibsp and parch.

Sibling:  Brother, Sister, Stepbrother, or Stepsister of Passenger Aboard
Titanic
Spouse:   Husband or Wife of Passenger Aboard Titanic (Mistresses and Fiances
Ignored)
Parent:   Mother or Father of Passenger Aboard Titanic
Child:    Son, Daughter, Stepson, or Stepdaughter of Passenger Aboard Titanic

Other family relatives excluded from this study include cousins,
nephews/nieces, aunts/uncles, and in-laws.  Some children travelled
only with a nanny, therefore parch=0 for them.  As well, some
travelled with very close friends or neighbors in a village, however,
the definitions do not support such relations.
```

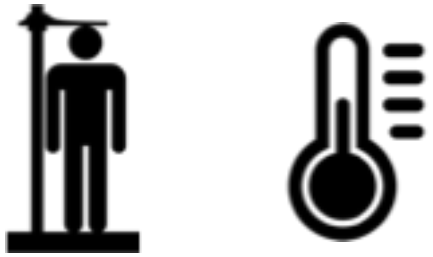
Metadata for Government Procurement

```
Identifier: '085dd6c3-387b-4661-ab26-02e422ad1286'
Name: 'government-procurement'
Title: 'Government Procurement'
Description: 'This dataset lists all open tenders put out by government
agencies since
  2015.'
Topics:
  - 'Finance'
Keywords:
  - 'GeBIZ'
  - 'procurement'
Publisher:
  Name: 'Ministry of Finance'
  Admin 1:
    Name: 'Charles Tan'
    Department: 'Performance & Resource Management'
    Email: 'Charles_TAN@mof.gov.sg'
Sources:
  - 'Ministry of Finance'
License: 'https://data.gov.sg/open-data-licence'
Frequency: 'Monthly'
Coverage: '2015-01-02 to 2017-01-31'
Last Updated: '2017-02-16T09:09:51.650638'
Resources:
  -
    Identifier: 'b9d8d509-5cb6-45dc-bb46-9508e670e3c2'
    Title: 'Government Procurement via GeBIZ'
    Url: 'https://storage.data.gov.sg/government-procurement/resources/
    government-procurement-via-gebiz-2016-11-22T11-45-37Z.csv'
    Format: 'CSV'
    Coverage: '2015-01-02 to 2017-01-31'
    Last Updated: '2016-11-22T11:45:37.105036'
```

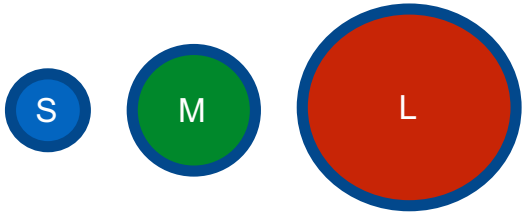
```
Url: 'https://storage.data.gov.sg/government-procurement/resources/
government-procurement-via-gebiz-2016-11-22T11-45-37Z.csv'
Format: 'CSV'
Coverage: '2015-01-02 to 2017-01-31'
Last Updated: '2016-11-22T11:45:37.105036'
Schema:
  -
    Name: 'tender_no.'
    Title: 'Tender No.'
    Type: 'text'
    Sub Type: 'general'
  -
    Name: 'agency'
    Title: 'Agency'
    Type: 'text'
    Sub Type: 'general'
  -
    Name: 'tender_description'
    Title: 'Tender Description'
    Type: 'text'
    Sub Type: 'general'
  -
    Name: 'award_date'
    Title: 'Award Date'
    Type: 'datetime'
    Sub Type: 'date'
    Format: 'YYYY-MM-DD'
  -
    Name: 'tender_detail_status'
    Title: 'Tender Detail Status'
    Type: 'text'
    Sub Type: 'general'
```

Variable Types

Numeric / Quantitative – values measured on a numerical scale e.g. height, income, temperature



Ordinal – values can be compared and ordered e.g. size (small, medium, large), attitudes (disagree, neutral, agree)



Categorical / Nominal – labels are not ordered e.g. nationality, occupation, movie genres

Class / Dummy Variables

- Let's say we have the categorical variable area, which takes on one of the following values: **`rural`**, **`suburban`**, and **`urban`**.
- We need to represent these numerically for a model. So how do we code them?
- How about **`0=rural`**, **`1=suburban`**, and **`2=urban`**?

Class / Dummy Variables

- But this implies an ordered relationship - is `urban` twice `suburban`? That doesn't make sense.
- However, we can represent this information by converting the one area variable into two new variables:

  `area_urban` and **`area_suburban`**.

Class / Dummy Variables

- We'll draw out how categorical variables can be represented without implying order.
- First, let's choose a reference category. This will be our "base" category.
- It's often good to choose the category with the largest sample size and a criteria that will help model interpretation. If we are testing for a disease, the reference category would be people without the disease.

Class / Dummy Variables

- Step 1: Select a reference category. We'll choose `rural` as our reference category.
- Step 2: Convert the values `rural`, `suburban`, and `urban` into a numeric representation that does not imply order.
- Step 3: Create two new variables: **`area_urban`** and **`area_suburban`**.

Class / Dummy Variables

- Why do we need only two dummy variables?

`rural`	`urban`	`suburban`

- We can derive all of the possible values from these two. If an area isn't `urban` or `suburban`, we know it must be `rural`.
- In general, if you have a categorical feature with k categories, you need to create k-1 dummy variable to represent all of the information.

Class / Dummy Variables

- Let's see our dummy variables.

	area_urban	area_suburban
rural	0	0
suburban	0	1
urban	1	0

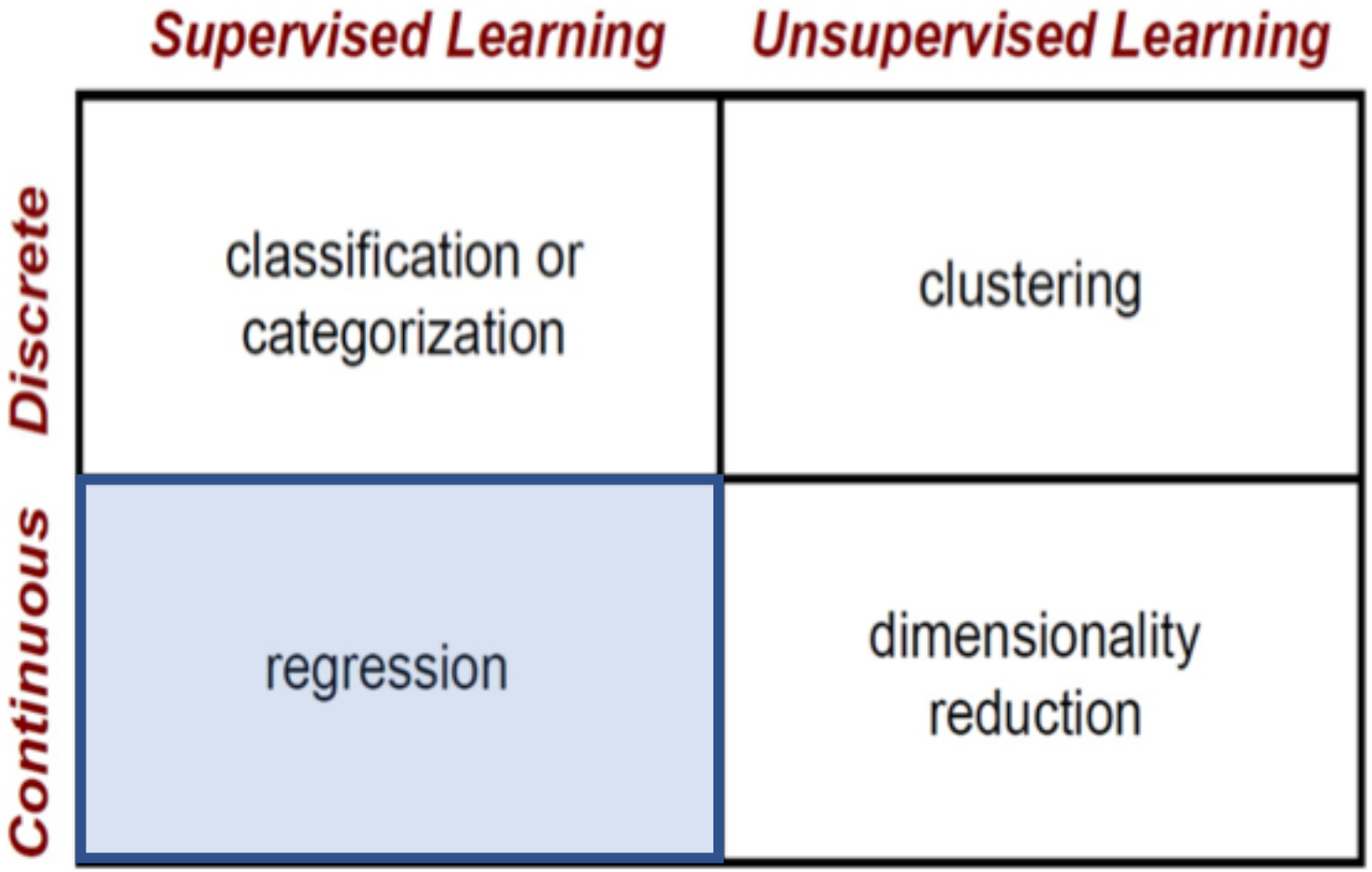
- As mentioned before, if we know `area_urban=0` and `area_suburban=0`, then the area must be rural.

Numpy and Pandas Introduction

- What are Numpy and Pandas? Python packages
- Pandas is built on Numpy
- Numpy uses arrays (lists) to do basic math and slice and index data
- Pandas uses a data structure called a Dataframe
- Dataframes are similar to Excel tables; they contain rows and columns
- With these packages, you can select pieces of data, do basic operations, calculate summary statistics

Machine Learning Algorithms

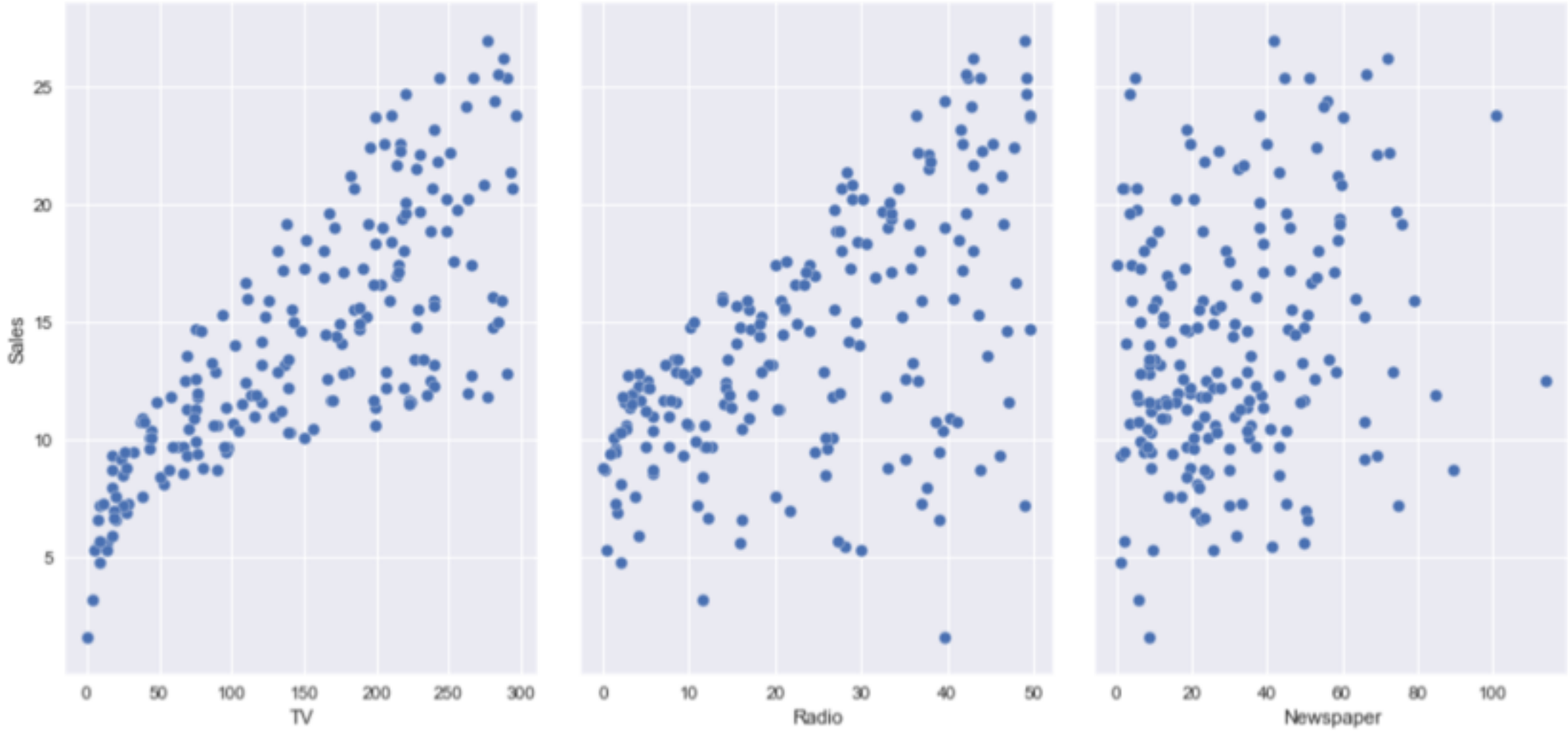
Machine Learning Categories



Linear Regression

- Linear regression is a simple approach to supervised learning. It assumes that the dependence of Y on X1, X2, … Xp is linear
- True regression functions however are never linear
- Despite these limitations, linear regression is still very useful conceptually and practically
- “Essentially, all models are wrong, but some are useful” – George Box
- “The only way to find out what will happen when a complex system is disturbed is to disturb the system, not merely to observe it passively” – Fred Mosteller and John Tukey

Linear Regression



Advertising dataset: Each observation represents one market

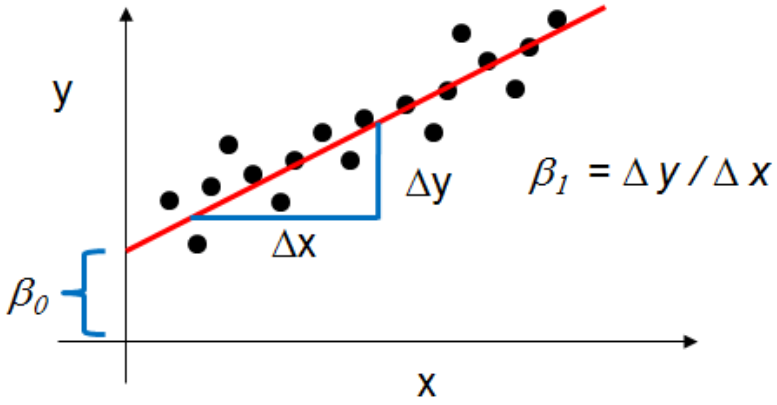
Linear Regression

Questions we might ask about the data:

- Is there a relationship between advertising and sales?
- How strong is the relationship?
- Which specific advertising types contribute to sales?
- What is the effect of each advertising type on sales?
- Given advertising spending in a particular market, can sales be predicted?

Linear Regression

- A simple linear model assumes the relationship: $Y = \beta_0 + \beta_1 X + \varepsilon$
- $\beta_0 \; and \; \beta_1$ are two unknown constants that represent the intercept and slope or also referred to as coefficients or parameters
- ε represents the error term
- Given estimates $\hat{\beta}_0$ and$\hat{\beta}_1$ for the model coefficients, we can predict future values using: $\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x + \varepsilon$

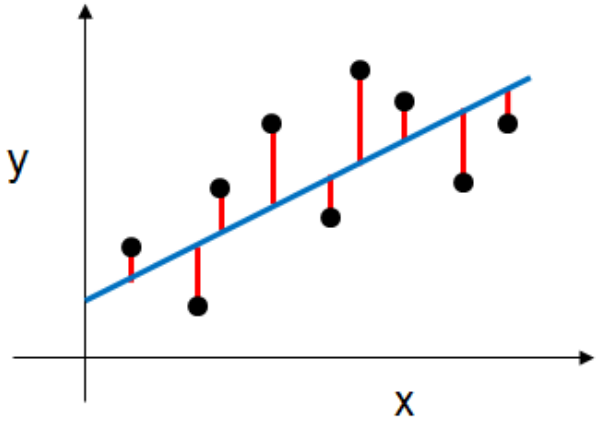


Linear Regression

- Let $\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_i + \varepsilon$ be the prediction for Y based on the *ith* value of X. Then $e_i = y_i - \hat{y}_i$ represents the *i*th residual
- We define the residual sum of squares (RSS) as: $RSS = e_1^2 + e_2^2 + \ldots e_n^2$
- The least squares approach chooses $\hat{\beta}_0$ and $\hat{\beta}_1$ to minimize the RSS
- The minimizing values can be shown to be:

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n}(x_i - x)(y_i - y)}{\sum_{i=1}^{n}(x_i - x)^2}$$

$$\hat{\beta}_0 = y - \hat{\beta}_1 x$$



Assessing Model Accuracy

- R-squared or fraction of variance explained is

$$R^2 = \frac{TSS - RSS}{TSS} = 1 - \frac{RSS}{TSS}$$

Where the total sum of squares $TSS = \sum_{i=1}^{n}(y_i - y)^2$

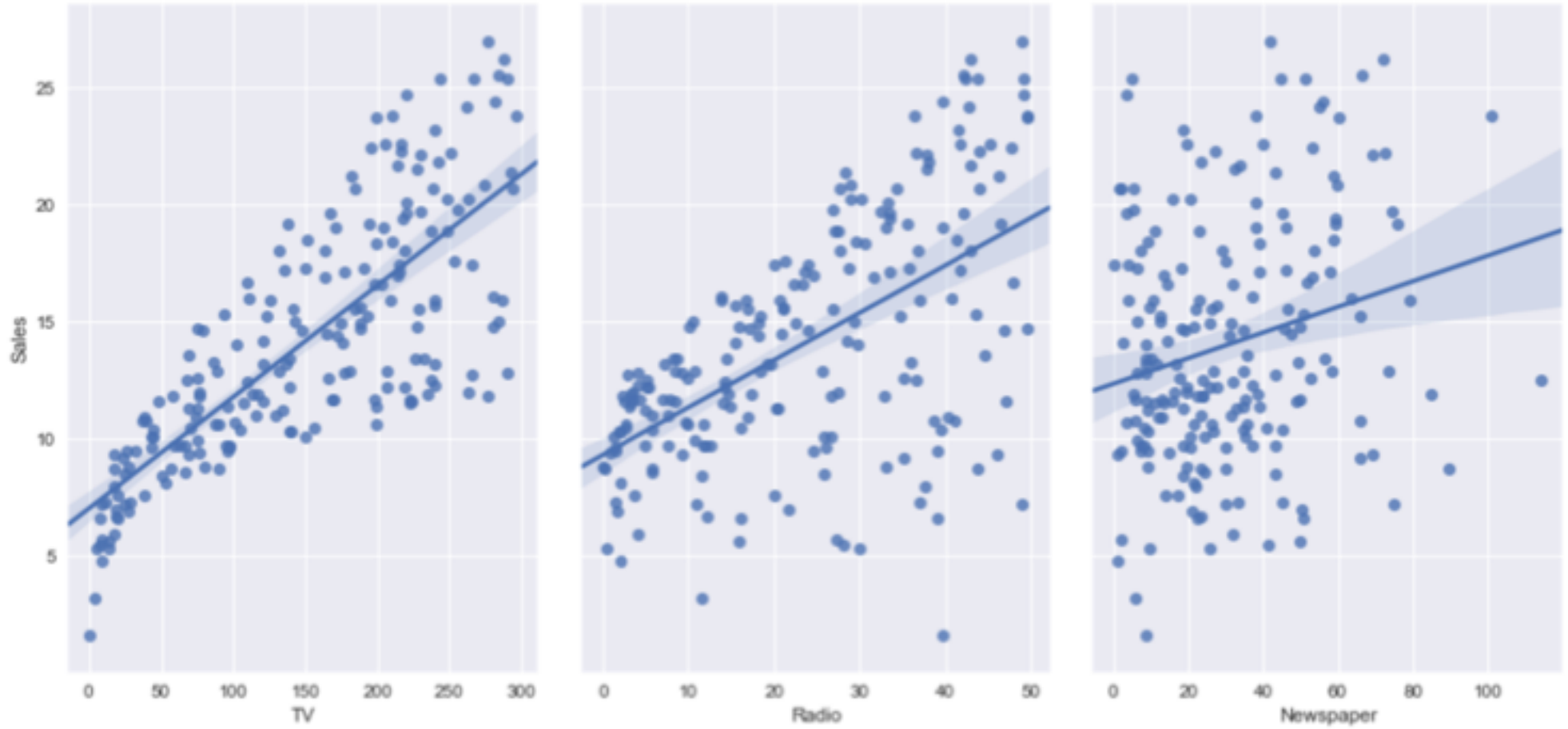
and the residual sum of squares is $RSS = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$

- It can be shown in the simple linear regression setting that

$R^2 = r^2$ where r is the correlation between X and Y:

$$r = \frac{\sum_{i=1}^{n}(x_i - x)(y_i - y)}{\sqrt{\sum_{i=1}^{n}(x_i - x)^2}\sqrt{\sum_{i=1}^{n}(y_i - y)^2}}$$

Linear Regression Single Predictor



Least squares regression fits for Sales against TV, Radio and Newspaper

Multiple Linear Regression

- A multiple linear model assumes the relationship:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon$$

- We interpret β_j as the average effect on Y due to a one unit increase in X_j while holding all other predictors constant

- In the advertising model, this equation becomes:

$$sales = \beta_0 + \beta_1 * TV + \beta_2 * Radio + \beta_3 * Newspaper + \varepsilon$$

- Similarly, we estimate $\beta_0, \beta_1, \ldots \beta_p$ as values that minimize the sum of square residuals

Multiple Linear Regression

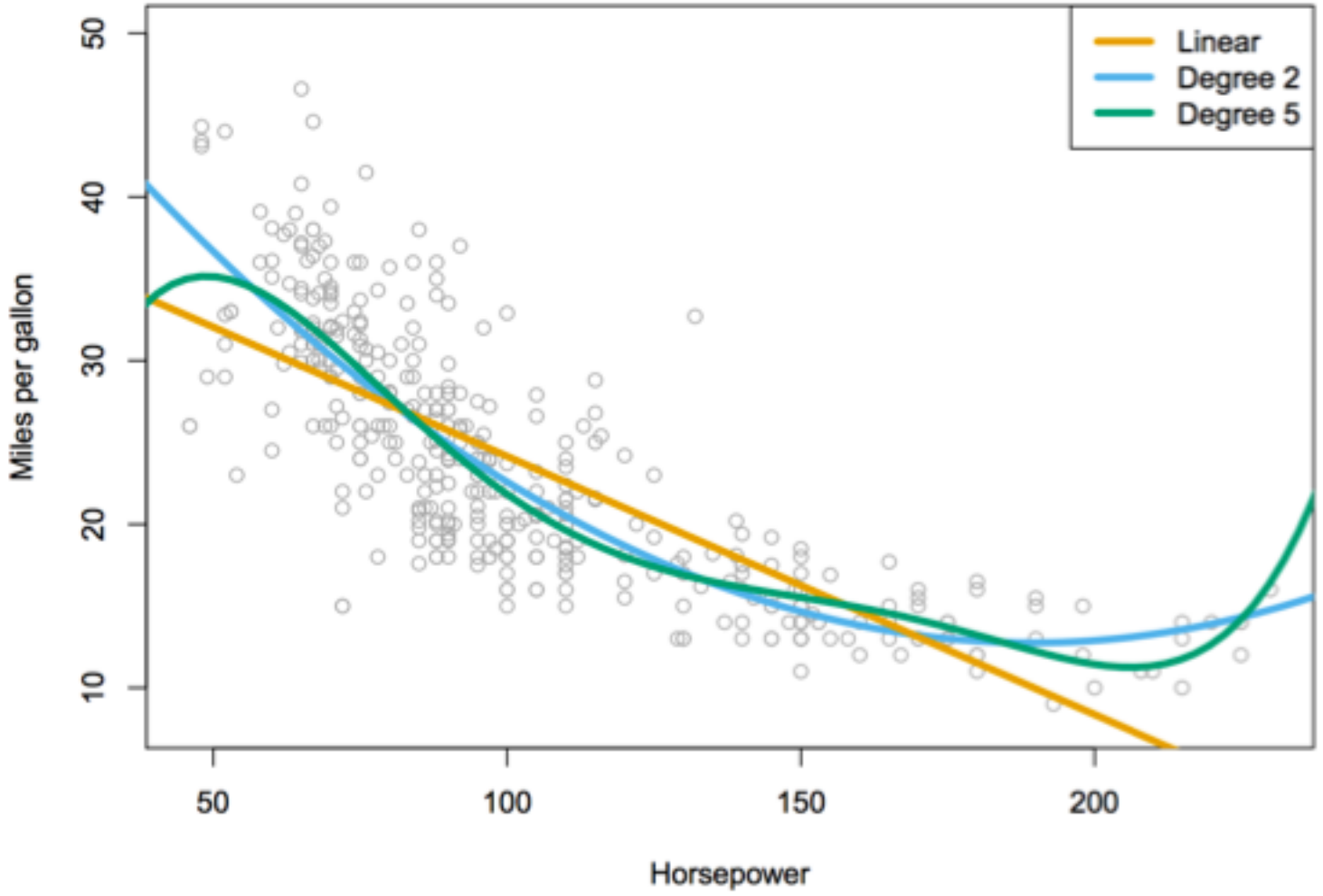
- Simple linear regression with one variable can explain some variance, but using multiple variables can be much more powerful.
- We want our multiple variables to be mostly independent to avoid multicollinearity.
- Multicollinearity, when two or more variables in a regression are highly correlated, can cause problems with the model.

Model Extensions: Interactions

- Suppose that spending money on radio advertising actually increases the effectiveness of TV advertising, thus the slope term for TV should increase as Radio increases
- In this scenario, given a fixed budget, spending half on Radio and half on TV may increase sales more than allocating the entire amount to either
- In business, this is known as the synergy effect, and in statistics it is referred to as an interaction effect
- Model takes the form:

$$sales = \beta_0 + \beta_1 * TV + \beta_2 * Radio + \beta_3 * (Radio * TV) + \varepsilon$$

Model Extensions: Polynomials



The figure suggests that including polynomial terms may provide a better fit

Linear Regression Analysis in Sklearn

- Sklearn defines models as objects (in the OOP sense).

You can use the following principles:

- All sklearn modeling classes are based on the base estimator. This means all models take a similar form.
- All estimators take a matrix X, either sparse or dense.
- Supervised estimators also take a vector y (the response).
- Estimators can be customized through setting the appropriate parameters.

Classes and Objects

- **Classes** are an abstraction for a complex set of ideas, e.g. human.
- Specific **instances** of classes can be created as **objects**.
  - john_smith = human()
- Objects have **properties**. These are attributes or other information.
  - john_smith.age
  - john_smith.gender
- Object have **methods**. These are procedures associated with a class/object.
  - john_smith.breathe()
  - john_smith.walk()

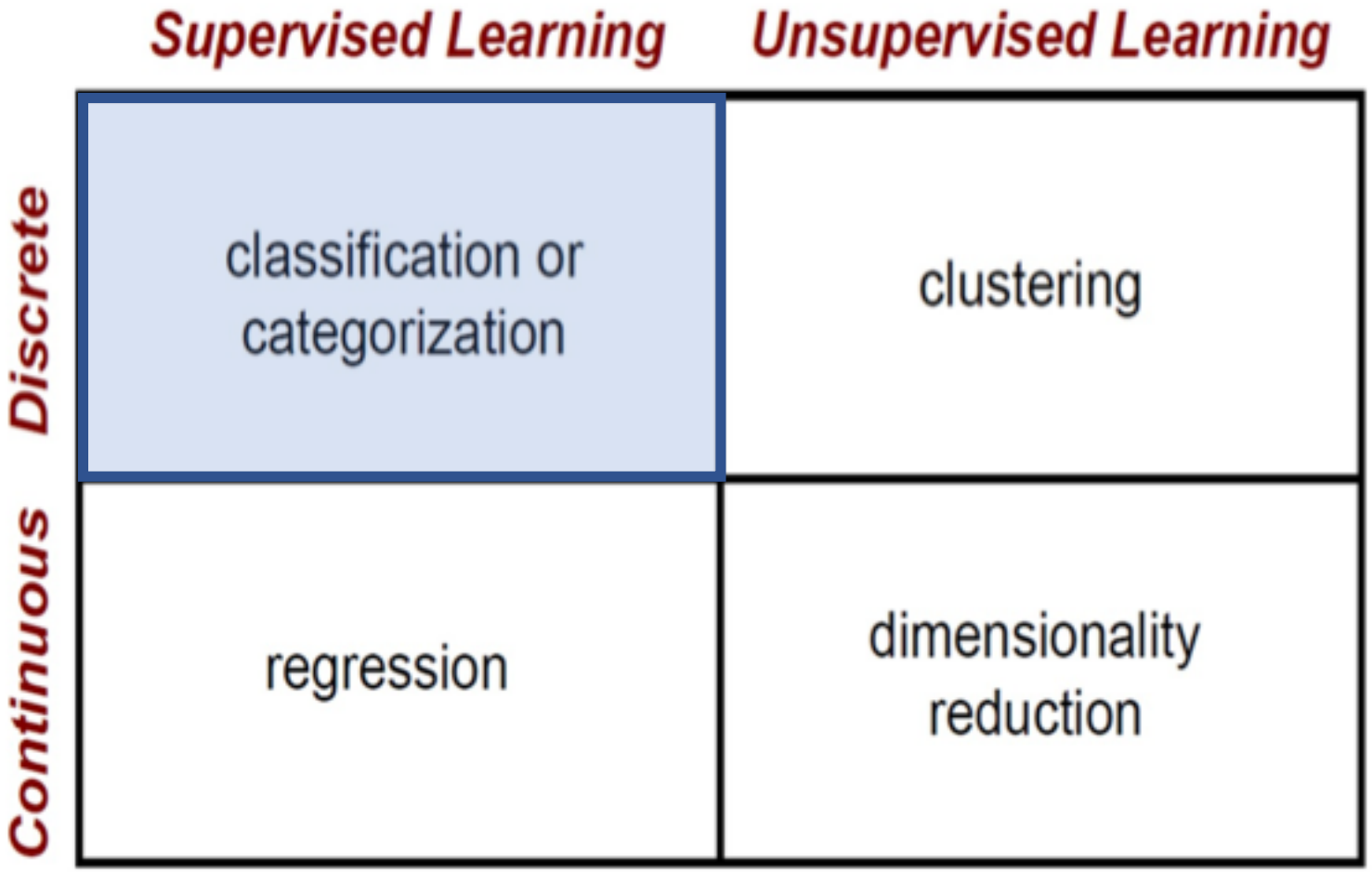
Linear Regression Analysis in Sklearn

- General format for sklearn model classes and methods

```
# generate an instance of an estimator class
estimator = base_models.AnySKLearnObject()
# fit your data
estimator.fit(X, y)
# score it with the default scoring method (recommended to use the metrics module in the future)
estimator.score(X, y)
# predict a new set of data
estimator.predict(new_X)
# transform a new X if changes were made to the original X while fitting
estimator.transform(new_X)
```

- LinearRegression() doesn't have a transform function
- With this information, we can build a simple process for linear regression.

Machine Learning Categories



What is Classification?

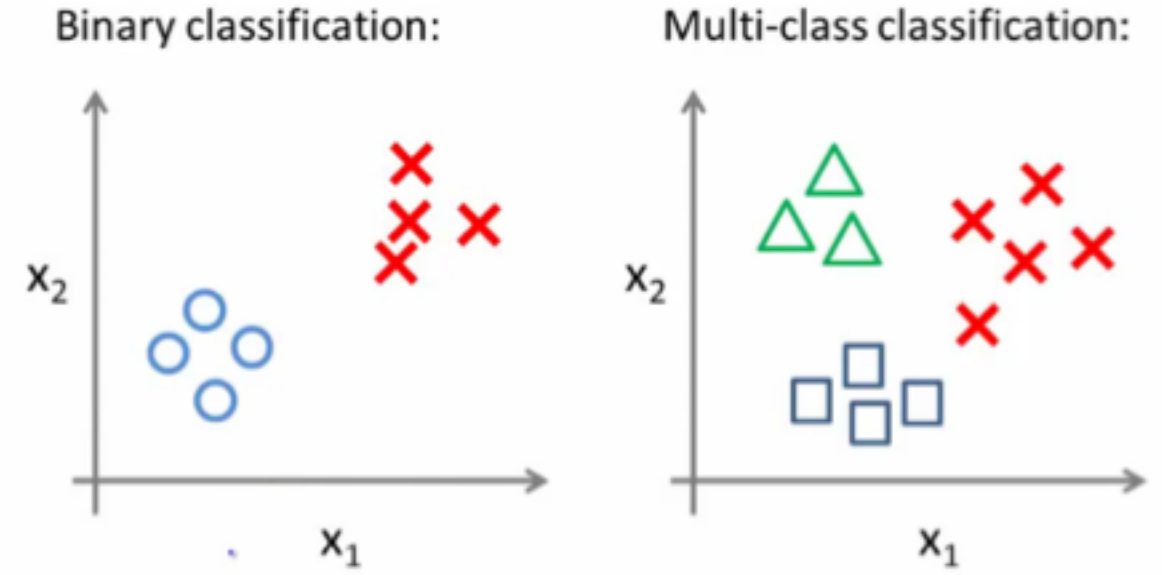
- Classification is a machine learning problem for solving a set value given the knowledge we have about that value.
- Many classification problems are trying to predict binary values.
- For example, we may be using patient data (medical history) to predict whether the patient is a smoker or not.

What is Classification?

- Some problems don't appear to be binary at first glance. However, you can boil down the response to a boolean (true/false) value.
- What if you are predicting whether an image pixel will be red or blue?
- We don't need to predict that a pixel is blue, just that it is not red.
- This is similar to the concept of dummy variables.

What is Classification?

- Binary classification is the simplest form of classification.
- However, classification problems can have multiple class labels.
- Instead of predicting whether the pixel is red or blue, you could predict whether the pixel is red, blue, or green.



What is a Class Label?

- A **class label** is a representation of what we are trying to predict: our target.
- Examples of class labels are:

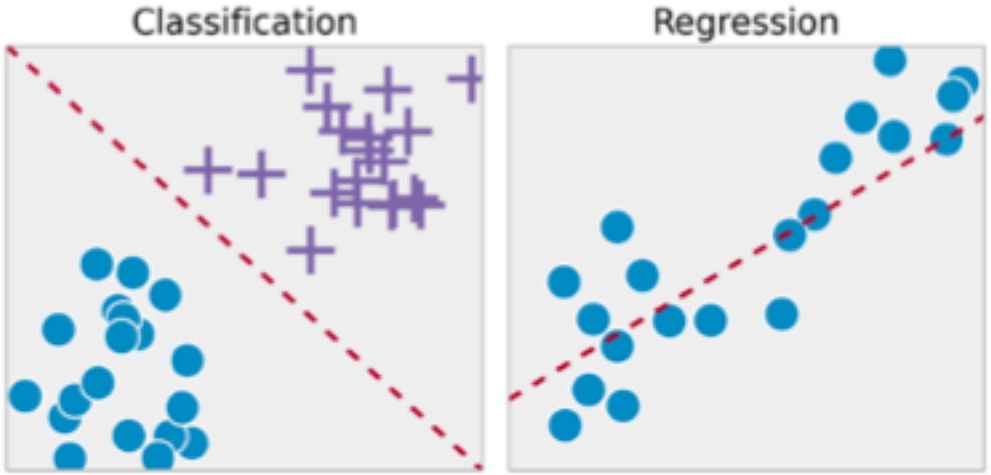
Data Problem	Class Labels
Patient data problem	is smoker, is not smoker
pixel color	red, blue, green

Determining Regression or Classification

- One of the easiest ways to determine if a problem is regression or classification is to determine if our target variable can be ordered mathematically.
- For example, if predicting company revenue, $100MM is greater than $90MM. This is a *regression* problem because the target can be ordered.
- However, if predicting pixel color, red is not inherently greater than blue. Therefore, this is a *classification* problem.

Logistic Regression

- Logistic regression is a linear approach to solving a classification problem
- That is, we can use a linear model, similar to Linear regression, in order to solve if an item belongs or does not belong to a class label
- Regression results can have a value range from -∞ to ∞
- Classification is used when predicted values (i.e. class labels) are not greater than or less than each other



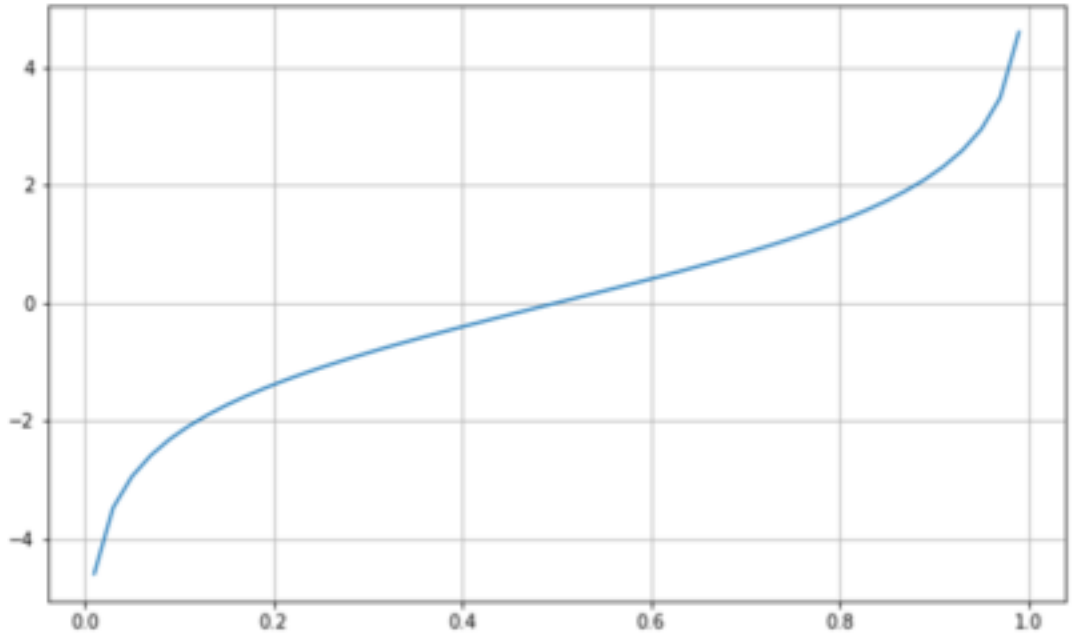
Logistic Regression

- The problem with using the linear regression equation to represent classification probabilities is predictions can be > 1 and < 0
- To avoid this problem, we use a function that gives outputs between 0 and 1 for all values of X

Log Odds: $\ln\left(\frac{p(X)}{1-p(X)}\right) = \beta_0 + \beta_1 X$

Odds: $\frac{p(X)}{1-p(X)} = e^{\beta_0+\beta_1 X}$

Probability: $p(X) = \frac{e^{\beta_0+\beta_1 X}}{1+e^{\beta_0+\beta_1 X}}$



Odds and Log-Odds

- The value within the natural log, $\frac{p}{1-p}$ represents the *odds*. Taking the natural log of odds generates *log odds*.
- Odds for an event – 5:2 reflects the event happening 5 times and not happening 2 times i.e. probability = 5/7
- The odds multiply by e^{β_1} for every 1-unit increase in x.

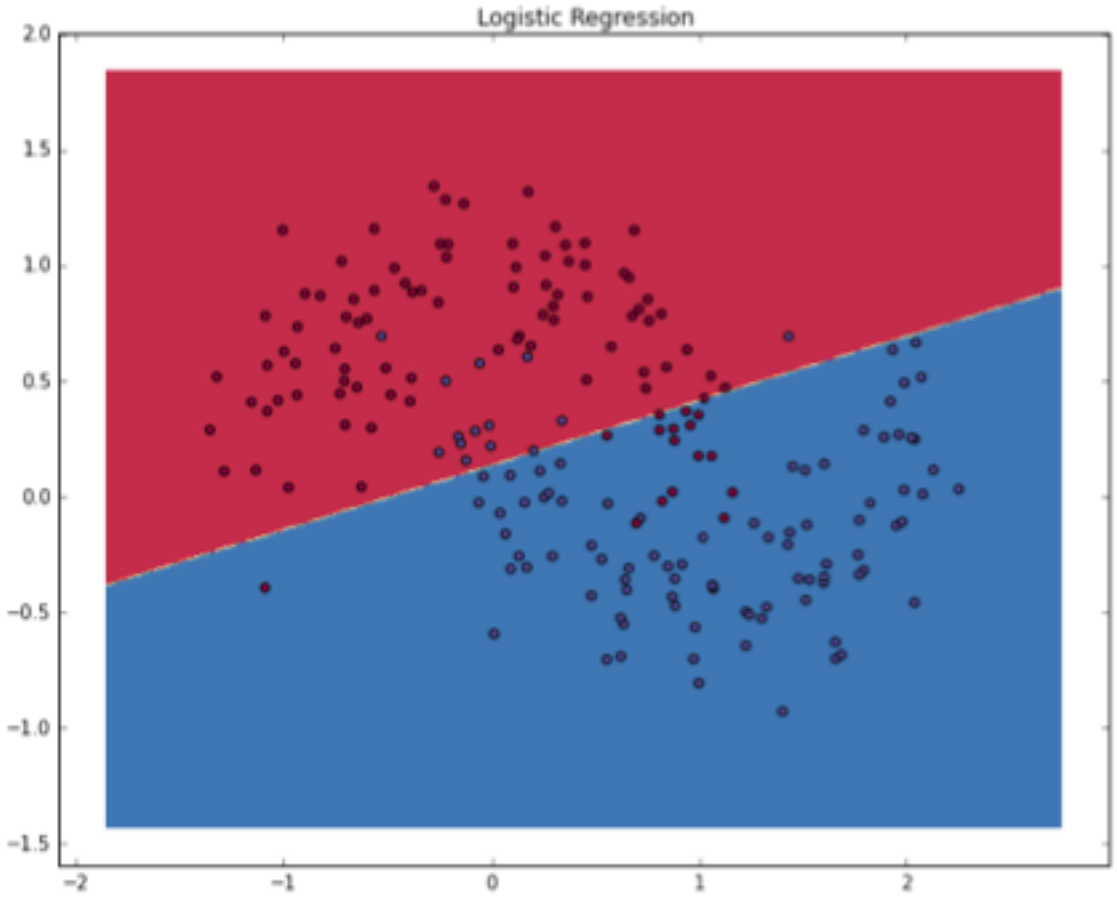
Odds and Log-Odds

- The coefficients are unknown and must be estimated based on the available training data
- Although we could use (non-linear) least squares to fit the model, the more general method of maximum likelihood is preferred since it has better statistical properties
- The basic intuition is that we seek estimates for the coefficients such that the predicted probability corresponds as closely to the actual observed value:

$$l(\beta_0, \beta_1) = \prod_{i:y_i=1} p(x_i) \prod_{i:y_i=0} (1 - p(x_i))$$

Odds and Log-Odds

With these coefficients, we get our overall probability: the logistic regression draws a linear decision line which divides the classes.



Classification Metrics

- Metrics for regression do **not** apply to classification.
- We could measure the distance between the probability of a given class and an item being in that class. Guessing 0.6 for a 1 is a 0.4 error.
- But this overcomplicates our goal: understanding binary classification, whether something is black or white, right or wrong.
- To do this, we'll measure "correctness" or "incorrectness".

Classification Metrics

- We'll use two primary metrics: *accuracy* and *misclassification rate*.
- **Accuracy** is the number of *correct* predictions out of all predictions in the sample. This is a value we want to *maximize*.
- **Misclassification rate** is the number of incorrect predictions out of all predictions in the sample. This is a value we want to *minimize*.
- These two metrics are directly opposite of each other.
- 1 - misclassification rate = accuracy