Kaggle Learning Course

이재욱, 이한나, 이나경, 이태경

Project Proposal

Topic | SQL / Deep Learning / Data Cleaning / AI / Geospatial Analysis

Description | Kaggle 에 있는 수업들을 수강하여 데이터 사이언스 안에 다양한 분야 (SQL, Deep Learning, AI Ethics, Geospatial Analysis, Game AI) 를 배울 이후 Kaggle 수업이 끝나면 배웠던 분야 중 제일 관심이 깊었던 분야에 관한 데이터 프로젝트를 진행할 예정

Expected Duration | 5 - 6 Week

Team Member | 이재욱, 이한나, 이나경, 이태경

Timeline

Week 5

- Project Proposal
- Lesson Overview

Week 6

- Intro to SQL
- Advanced SQL

Week 7

- Deep Learning
- Data Cleaning

Week 8

- Time Series
- Geospatial Analysis

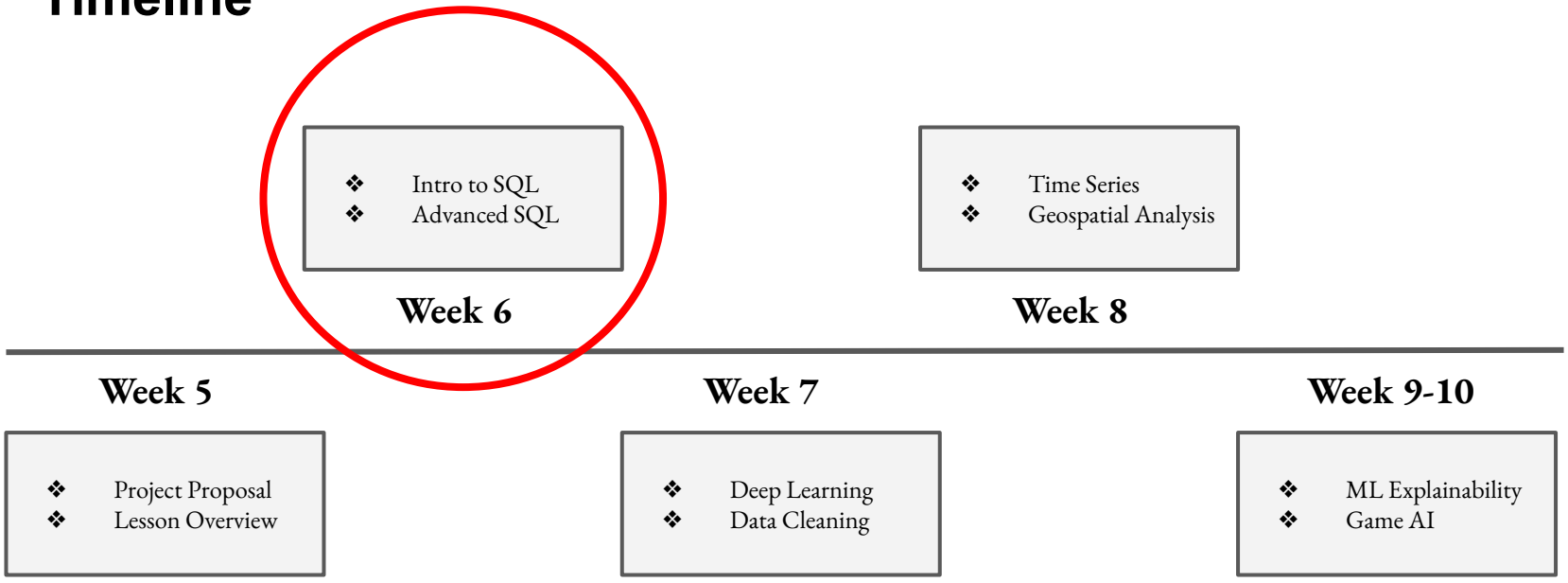
Week 9-10

- ML Explainability
- Game AI

SQL and BigQuery

이재욱, 이한나, 이나경, 이태경

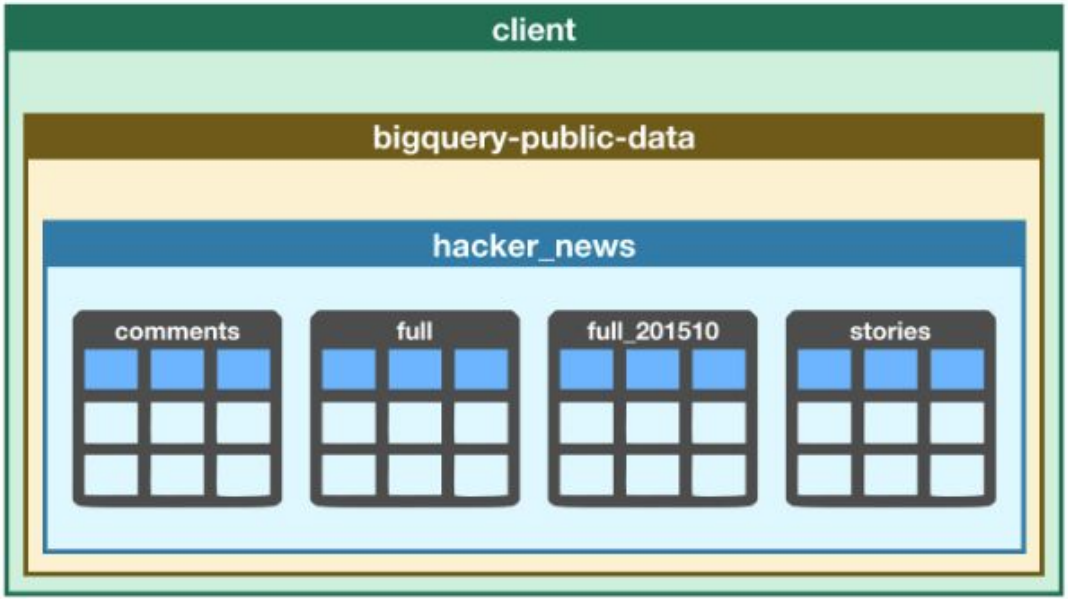
Timeline


Intro to SQL
Advanced SQL
Week 6
Time Series
Geospatial Analysis
Week 8
Week 5
Project Proposal
Lesson Overview
Week 7
Deep Learning
Data Cleaning
Week 9-10
ML Explainability
Game AI

SQL vs Python

SQL	Python
● Programming language to manage and retrieve data from databases ● Focus is to ‘create’ and ‘maintain’ the datasets ● Access and extract data from database ● Not designed for high level data ● Industry Standard ● Querying data is faster than Python (Simple)	● Analyze and manipulate data ● Specifically designed to create applications

SQL Structure



Client objects hold projects and a connection to the BigQuery service.

bigquery-public-data is a **project**. A project is a collection of datasets.

hacker_news is a **dataset**. A dataset is a collection of tables.

comments, *full*, *full_201510*, and *stories* are **tables**.

Select, From, Where

: get data from specifically based on conditions

```
query = """
        SELECT Name
        FROM `bigquery-public-data.pet_records.pets`
        WHERE Animal = 'Cat'
        """
```

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
2	Moon	Dog
3	Ripley	Cat
4	Tom	Cat

Group By, Having & Count

: to group data and count things within those groups

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
2	Moon	Dog
3	Ripley	Cat
4	Tom	Cat

```
query = """
        SELECT COUNT(ID)
        FROM `bigquery-public-data.pet_records.pets`
        """
```

f0_
4

```
query = """
        SELECT Animal, COUNT(ID)
        FROM `bigquery-public-data.pet_records.pets`
        GROUP BY Animal
        """
```

Animal	f0_
Rabbit	1
Dog	1
Cat	2

Group By, Having & Count

: to group data and count things within those groups

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
2	Moon	Dog
3	Ripley	Cat
4	Tom	Cat

```
query = """
        SELECT Animal, COUNT(ID)
        FROM `bigquery-public-data.pet_records.pets`
        GROUP BY Animal
        HAVING COUNT(ID) > 1
        """
```

Animal	f0_
Cat	2

Order By

: sorts the results returned by the rest of your query

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
4	Tom	Cat
2	Moon	Dog
3	Ripley	Cat

```
query = """
        SELECT ID, Name, Animal
        FROM `bigquery-public-data.pet_records.pets`
        ORDER BY ID
        """
```

ID	Name	Animal
1	Dr. Harris Bonkers	Rabbit
2	Moon	Dog
3	Ripley	Cat
4	Tom	Cat

JOIN and UNIONS

`owners` table

ID	Name	Age	Pet_ID
1	Aubrey Little	20	1
2	Chett Crawfish	45	3
3	Jules Spinner	10	4
4	Magnus Burnsides	9	2
5	Veronica Dunn	8	NULL

`pets` table

ID	Name	Age	Animal
1	Dr. Harris Bonkers	1	Rabbit
2	Moon	9	Dog
3	Ripley	7	Cat
4	Tom	2	Cat
5	Maisie	10	Dog

Dr. Harris Bonkers is owned by **Aubrey Little**.

Moon is owned by **Magnus Burnsides**.

Ripley is owned by **Chett Crawfish**.

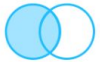
Tom is owned by **Jules Spinner**.

Veronica Dunn does not have a pet.
Maisie does not have an owner.

INNER JOIN

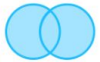
Owner_Name	Pet_Name
Aubrey Little	Dr. Harris Bonkers
Magnus Burnsides	Moon
Chett Crawfish	Ripley
Jules Spinner	Tom

LEFT JOIN



Owner_Name	Pet_Name
Aubrey Little	Dr. Harris Bonkers
Magnus Burnsides	Moon
Chett Crawfish	Ripley
Jules Spinner	Tom
Veronica Dunn	NULL

FULL JOIN



Owner_Name	Pet_Name
Aubrey Little	Dr. Harris Bonkers
Magnus Burnsides	Moon
Chett Crawfish	Ripley
Jules Spinner	Tom
Veronica Dunn	NULL
NULL	Maisie

UNION

```
query = """
        SELECT Age FROM `bigquery-public-data.pet_records.pets`
        UNION ALL
        SELECT Age FROM `bigquery-public-data.pet_records.owners`
        """
```

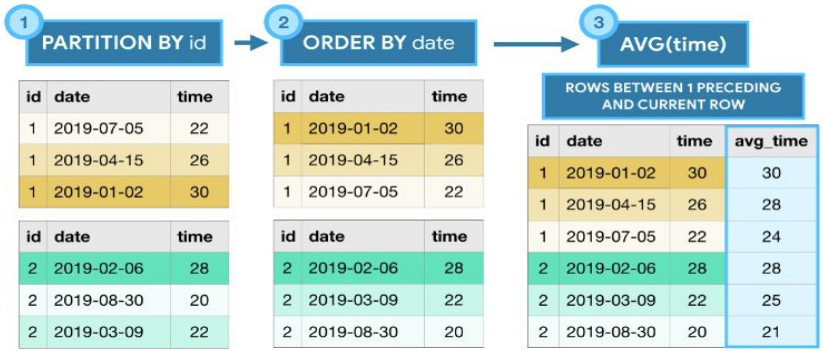
Age
20
45
10
9
8
1
9
7
2
10

Analytic Functions

id	date	time
1	2019-07-05	22
1	2019-04-15	26
2	2019-02-06	28
1	2019-01-02	30
2	2019-08-30	20
2	2019-03-09	22

```
query = """
        SELECT *,
            AVG(time) OVER(
                                PARTITION BY id
                                ORDER BY date
                                ROWS BETWEEN 1 PRECEDING AND CURRENT ROW
                                ) as avg_time
        FROM `bigquery-public-data.runners.train_time`
        """
```

id	date	time
1	2019-07-05	22
1	2019-04-15	26
2	2019-02-06	28
1	2019-01-02	30
2	2019-08-30	20
2	2019-03-09	22



id	date	time
1	2019-07-05	22
1	2019-04-15	26
1	2019-01-02	30

id	date	time
2	2019-02-06	28
2	2019-08-30	20
2	2019-03-09	22

id	date	time
1	2019-01-02	30
1	2019-04-15	26
1	2019-07-05	22

id	date	time
2	2019-02-06	28
2	2019-03-09	22
2	2019-08-30	20

id	date	time	avg_time
1	2019-01-02	30	30
1	2019-04-15	26	28
1	2019-07-05	22	24
2	2019-02-06	28	28
2	2019-03-09	22	25
2	2019-08-30	20	21

Analytic Functions

Aggregate

- MIN / MAX
- AVG / SUM
- COUNT

Navigation

- FIRST_VALUE / LAST
- LEAD / LAG

Numbering

- ROW_NUMBER
- RANK

Nested and Repeated Data

Nested Fields

- Nested columns have type **STRUCT**

Repeated Fields

- Table permits more than **one value** for each row

Nested & Repeated

- Table Combines nested and repeated fields denormalized many relationship without joins

`pets` table

ID	Name	Age	Animal
1	Moon	9	Dog
2	Ripley	7	Cat
3	Napoleon	1	Fish

`toys` table

ID	Name	Type	Pet_ID
1	McFly	Frisbee	1
2	Fluffy	Feather	2
3	Eddy	Castle	3

vs.

`pets_and_toys` table

ID	Name	Age	Animal	Toy
1	Moon	9	Dog	{**Name**: McFly, **Type**: Frisbee}
2	Ripley	7	Cat	{**Name**: Fluffy, **Type**: Feather}
3	Napoleon	1	Fish	{**Name**: Eddy, **Type**: Castle}

`pets` table

ID	Name	Age	Animal
1	Moon	9	Dog
2	Ripley	7	Cat
3	Napoleon	1	Fish

`toys_type` table

ID	Type	Pet_ID
1	Frisbee	1
2	Bone	1
3	Rope	1
4	Feather	2
5	Ball	2
6	Castle	3

vs.

`pets_and_toys_type` table

ID	Name	Age	Animal	Toys
1	Moon	9	Dog	[Frisbee, Bone, Rope]
2	Ripley	7	Cat	[Feather, Ball]
3	Napoleon	1	Fish	[Castle]

`pets` table

ID	Name	Age	Animal
1	Moon	9	Dog
2	Ripley	7	Cat
3	Napoleon	1	Fish

`more_toys` table

ID	Name	Type	Pet_ID
1	McFly	Frisbee	1
2	Scully	Bone	1
3	Pusheen	Rope	1
4	Fluffy	Feather	2
5	Robert	Ball	2
6	Eddy	Castle	3

vs.

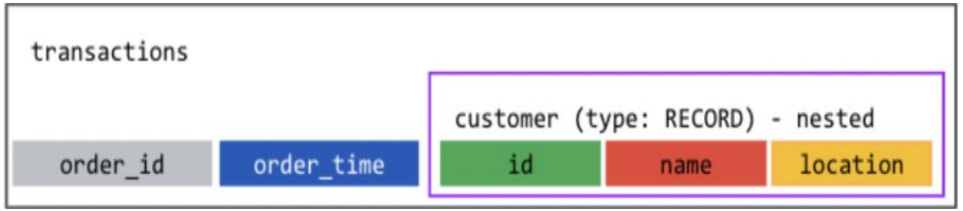
`more_pets_and_toys` table

ID	Name	Age	Animal	Toys
1	Moon	9	Dog	[{**Name**: McFly, **Type**: Frisbee}, {**Name**: Scully, **Type**: Bone}, {**Name**: Pusheen, **Type**: Rope}]
2	Ripley	7	Cat	[{**Name**: Fluffy, **Type**: Feather}, {**Name**: Robert, **Type**: Ball}]
3	Napoleon	1	Fish	[{**Name**: Eddy, **Type**: Castle}]

Nested and Repeated Data

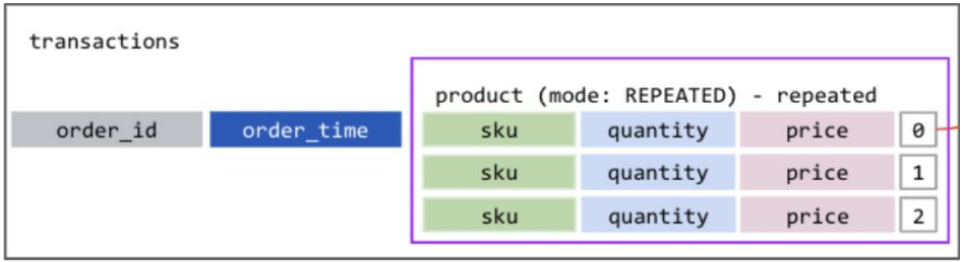
Nested Fields

- Table is collapsed into a single column



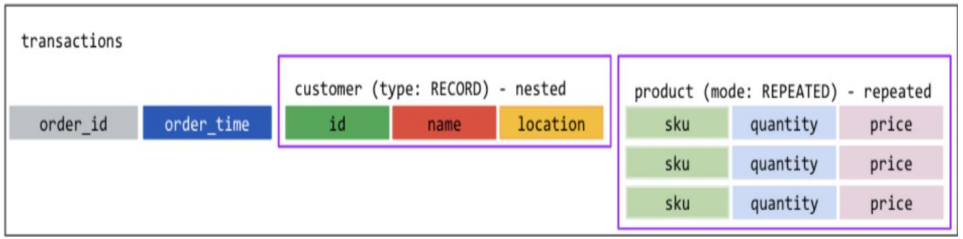
Repeated Fields

- Permits more than one value for each row



Nested & Repeated

- Combining nested and repeated fields denormalized many relationship without joins



Writing Efficient Queries

- Database systems have a **query optimizer** that attempts to interpret/execute query in the most effective way
    - *show_amount_of_data_scanned()* shows the amount of data query used
    - *show_time_to_run() prints* how long it takes for the query to execute
- Strategies
    - Only select the columns you want
    - SELECT * FROM

```
star_query = "SELECT * FROM `bigquery-public-data.github_repos.contents`"
show_amount_of_data_scanned(star_query)

basic_query = "SELECT size, binary FROM `bigquery-public-data.github_repos.content
s`"
show_amount_of_data_scanned(basic_query)
```

```
Data processed: 2623.284 GB
Data processed: 2.466 GB
```

Deep Learning & Data Cleaning

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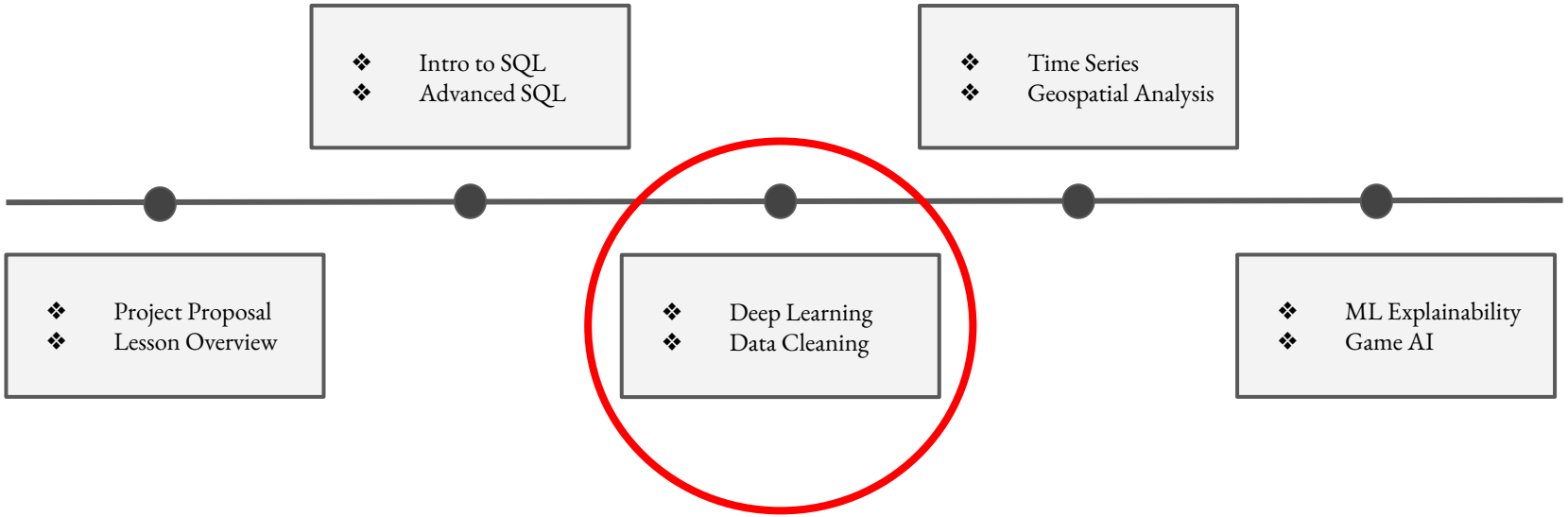
Timeline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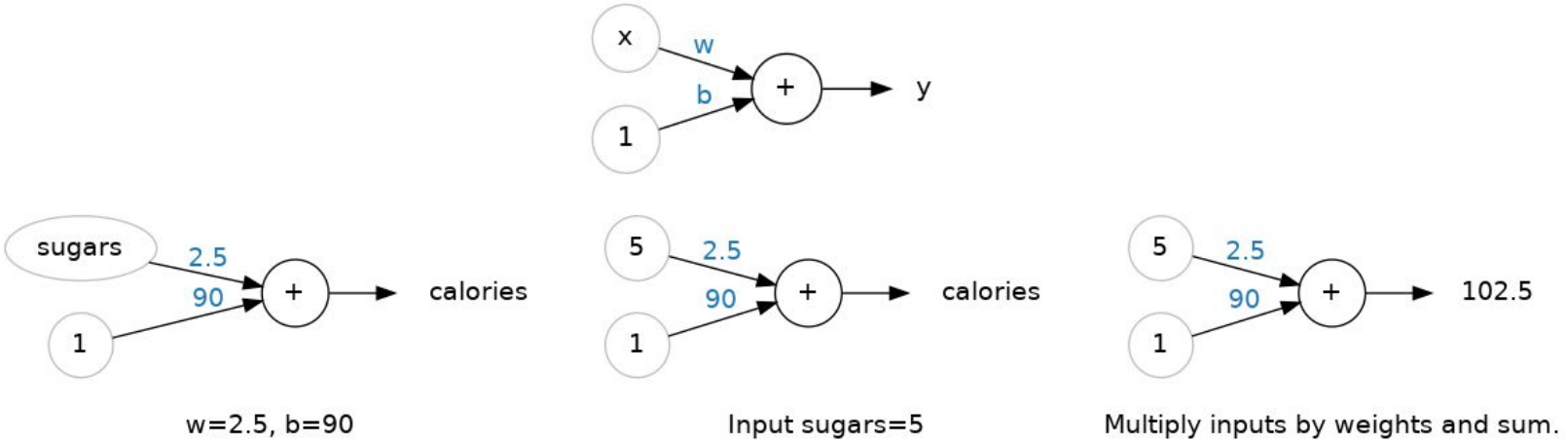
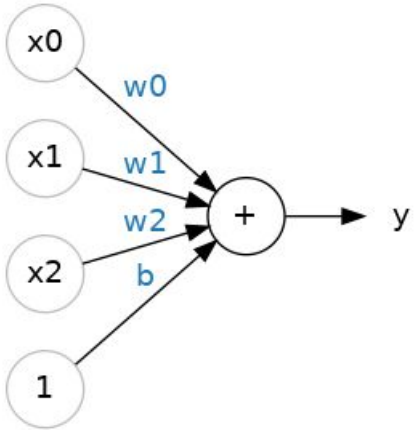
Deep Learning

Approach to Machine Learning characterized by stacks of computations

Neural Networks - Defining model of Deep Learning

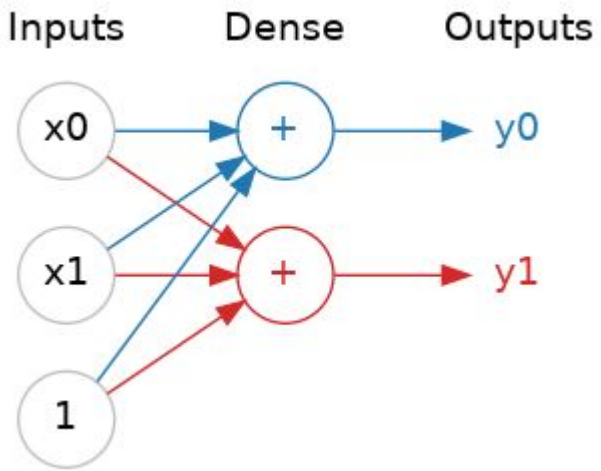


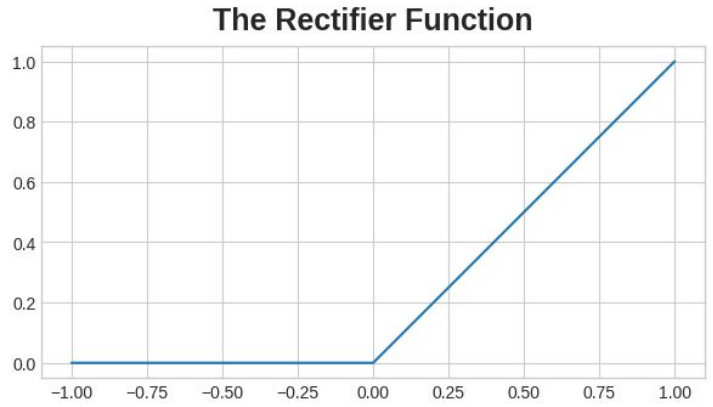
Keras

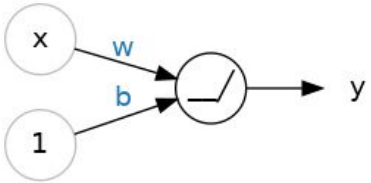



```
from tensorflow import keras
from tensorflow.keras import layers

#Network with 1 linear unit
model = keras.Sequential([
    layers.Dense(units=1,
input_shape=[3])
])
```

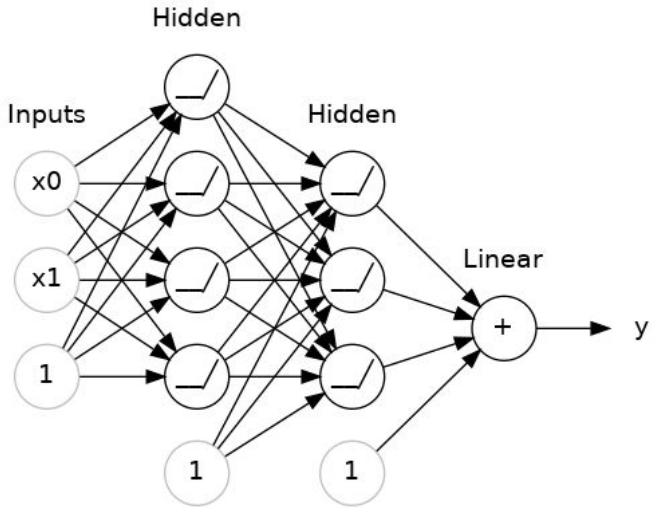
Multiple Layers & Activation Functions





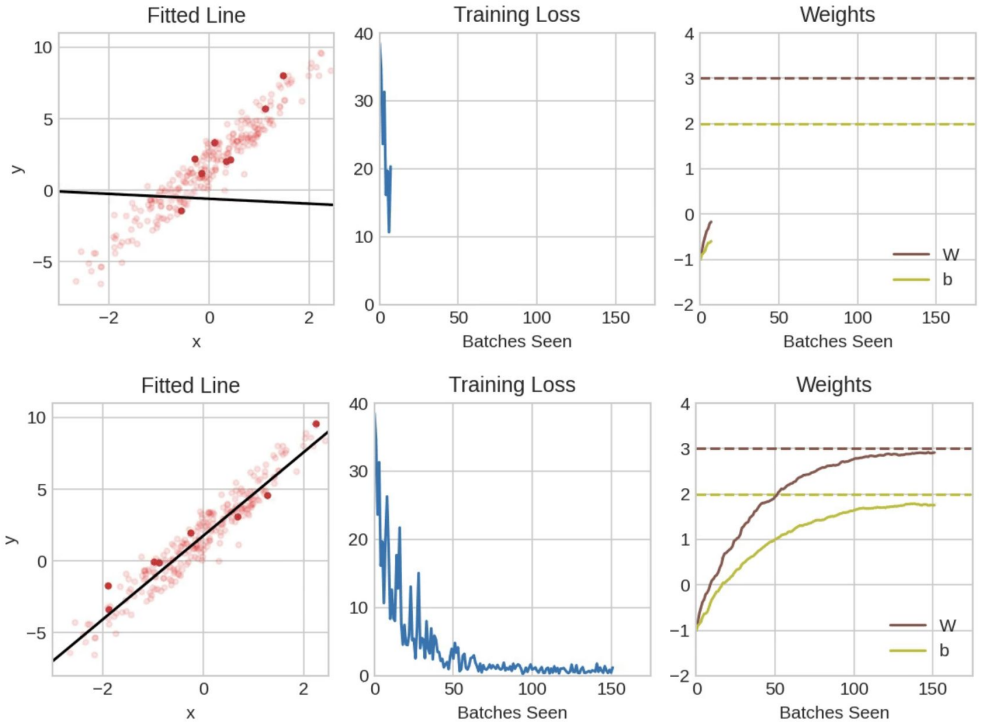


Multiple Layers & Activation Functions



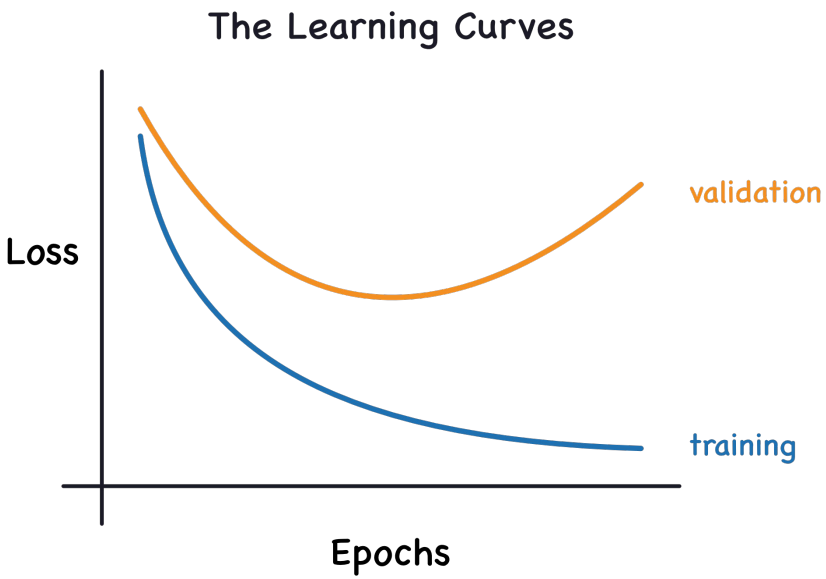

```
from tensorflow import keras
from tensorflow.keras import layers

model = keras.Sequential([
    # the hidden ReLU layers
    layers.Dense(units=4, activation='relu', input_shape=[2]),
    layers.Dense(units=3, activation='relu'),
    # the linear output layer
    layers.Dense(units=1),
])
```

Stochastic Gradient Descent




```
from tensorflow import keras
from tensorflow.keras import layers

model.compile(
    optimizer="adam",
    loss="mae",
  )

history = model.fit(
    X_train, y_train,
    validation_data=(X_valid, y_valid),
    batch_size=256,
    epochs=10,
)
```

Overfitting and Underfitting

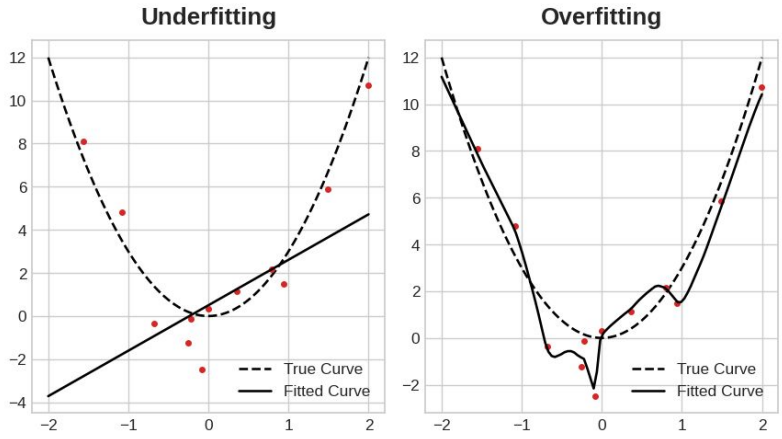


Validation loss gives an estimate of the expected error on data

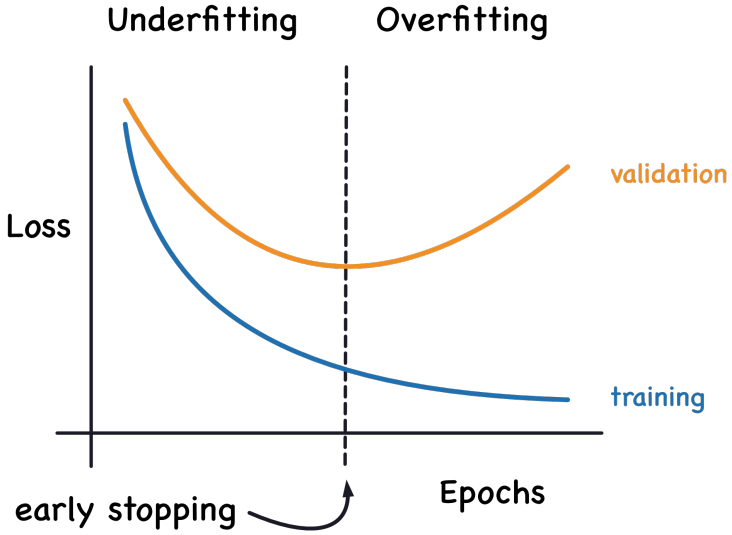
Training Data: **signal** and **noise**

Signal: Generalize to predict new data

Noise: Part that is only true of the training data



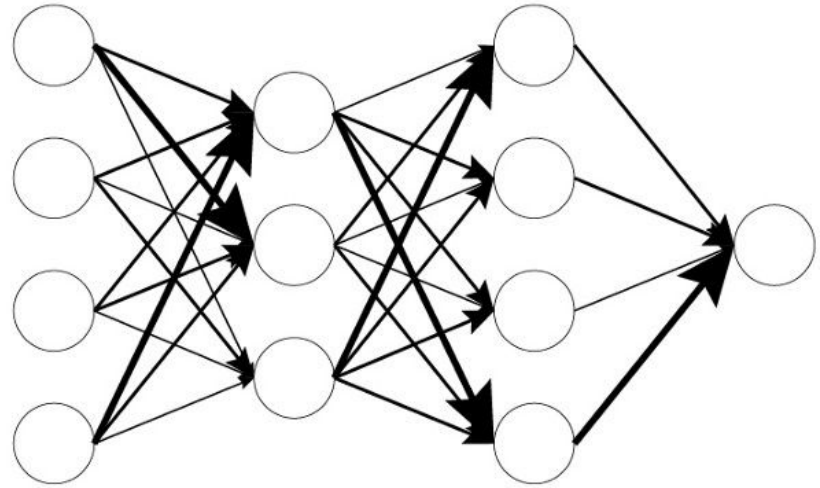
Overfitting and Underfitting




```python
from tensorflow.keras.callbacks import EarlyStopping

early_stopping = EarlyStopping(
    min_delta=0.001, # minimium amount of change to count as an improvement
    patience=20, # how many epochs to wait before stopping
    restore_best_weights=True,
)
```

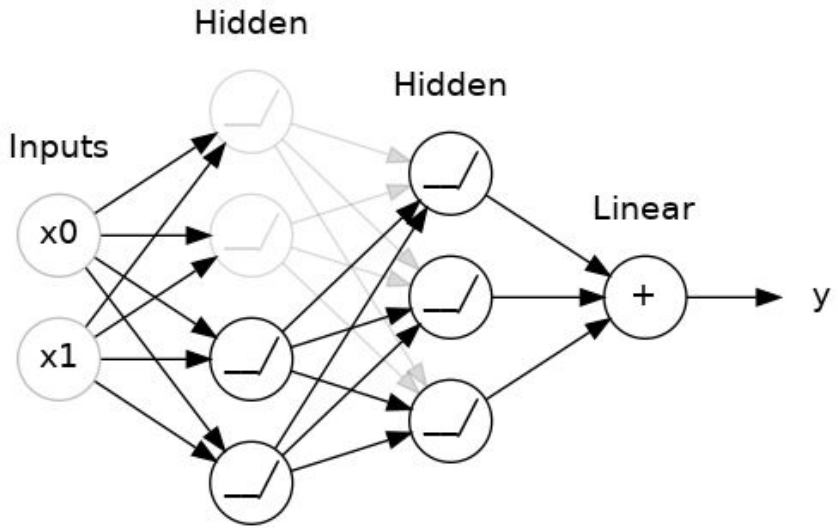
We keep the model where the validation loss is at a minimum

Batch Normalization



- **Raw** signal
- **High interdependancy** between distributions
- **Slow** and **unstable** training

Batch Normalization




```
layers.Dense(16),
layers.BatchNormalization(),
layers.Activation('relu'),
```

Data Cleaning (Handling Missing Values)

```
# get the number of missing data points per column
missing_values_count = nfl_data.isnull().sum()

# look at the # of missing points in the first ten columns
missing_values_count[0:10]
```

```
Date               0
GameID             0
Drive              0
qtr                0
down           61154
time             224
TimeUnder          0
TimeSecs         224
PlayTimeDiff     444
SideofField      528
dtype: int64
```

Is this value missing because it wasn't recorded
or
because it doesn't exist?

From dataset of events that occured in American Football games

Data Cleaning (Handling Missing Values)

Drop Missing Value:

```
# remove all the rows that contain a missing value
nfl_data.dropna()
```

:

	Date	GameID	Drive	qtr	down	time	TimeUnder	TimeSecs	PlayTimeDiff	SideofField	...	yacEPA

From dataset of events that occured in American Football games

Data Cleaning (Handling Missing Values)

Fill Missing Value:

```
# replace all NA's with 0
subset_nfl_data.fillna(0)
```

	EPA	airEPA	yacEPA	Home_WP_pre	Away_WP_pre	Home_WP_post	Away_WP_post	Wir
0	2.014474	0.000000	0.000000	0.485675	0.514325	0.546433	0.453567	0.4
1	0.077907	-1.068169	1.146076	0.546433	0.453567	0.551088	0.448912	0.5
2	-1.402760	0.000000	0.000000	0.551088	0.448912	0.510793	0.489207	0.5
3	-1.712583	3.318841	-5.031425	0.510793	0.489207	0.461217	0.538783	0.5
4	2.097796	0.000000	0.000000	0.461217	0.538783	0.558929	0.441071	0.4

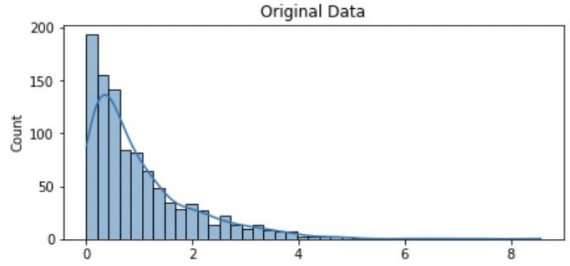
```
# replace all NA's the value that comes directly after it in the same column,
# then replace all the remaining na's with 0
subset_nfl_data.fillna(method='bfill', axis=0).fillna(0)
```

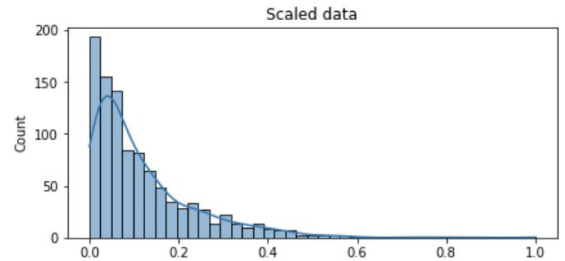
	EPA	airEPA	yacEPA	Home_WP_pre	Away_WP_pre	Home_WP_post	Away_WP_post	Wir
0	2.014474	-1.068169	1.146076	0.485675	0.514325	0.546433	0.453567	0.4
1	0.077907	-1.068169	1.146076	0.546433	0.453567	0.551088	0.448912	0.5
2	-1.402760	3.318841	-5.031425	0.551088	0.448912	0.510793	0.489207	0.5
3	-1.712583	3.318841	-5.031425	0.510793	0.489207	0.461217	0.538783	0.5
4	2.097796	0.000000	0.000000	0.461217	0.538783	0.558929	0.441071	0.4

From dataset of events that occured in American Football games

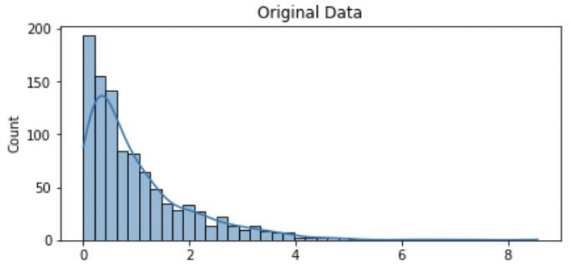
Scaling and Normalization

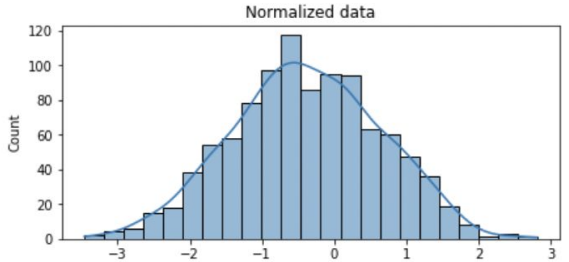
```
# generate 1000 data points randomly drawn from an exponential distribution
original_data = np.random.exponential(size=1000)

# mix-max scale the data between 0 and 1
scaled_data = minmax_scaling(original_data, columns=[0])
```






```
# normalize the exponential data with boxcox
normalized_data = stats.boxcox(original_data)
```

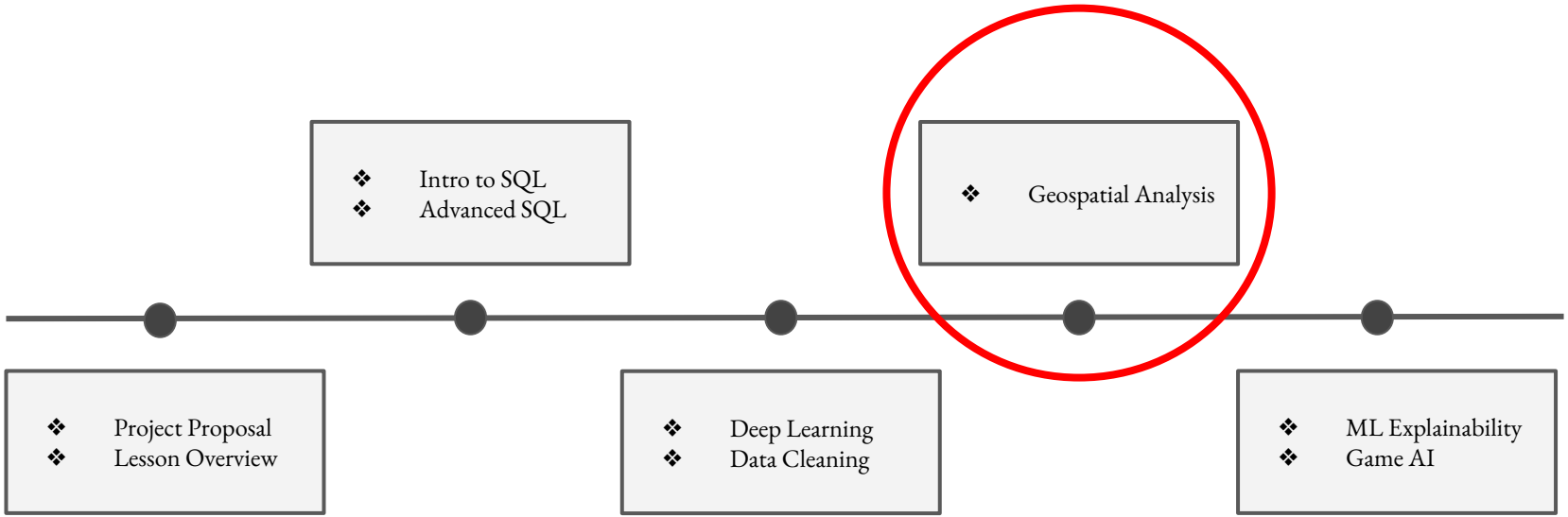




Geospatial Analysis

이재욱, 이한나, 이나경, 이태경

Timeline


Intro to SQL
Advanced SQL
Geospatial Analysis
Project Proposal
Lesson Overview
Deep Learning
Data Cleaning
ML Explainability
Game AI

Geospatial Analysis

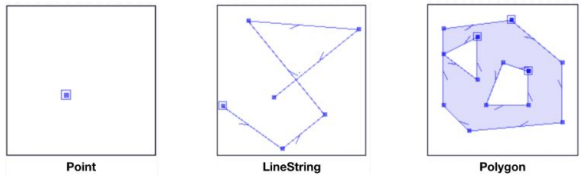
In [1]:
```
import geopandas as gpd
```

- Shapefile
- GeoJSON
- KML
- GPKG

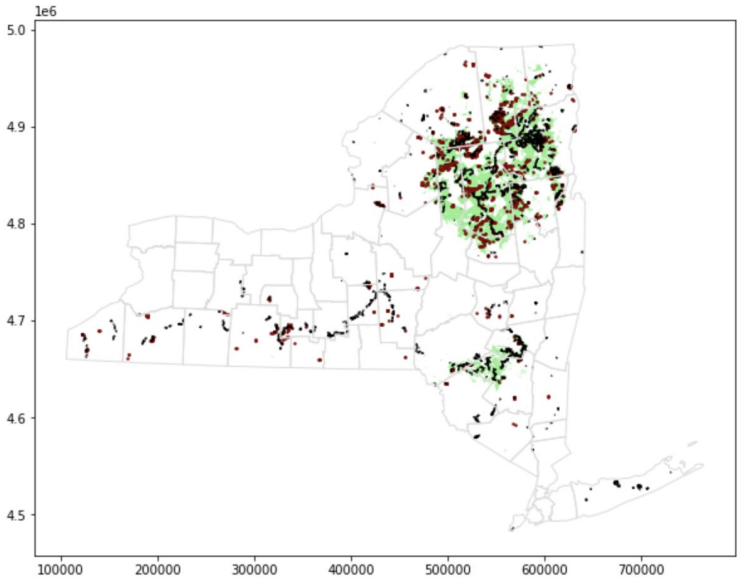
```
full_data = gpd.read_file
```

UPDATE_	OFFICE	ACRES	LANDS_UID	GREENCERT	SHAPE_AREA	SHAPE_LEN
5/12	STAMFORD	738.620192	103	N	2.990365e+06	7927.662385
5/12	STAMFORD	282.553140	1218	N	1.143940e+06	4776.375600
5/12	STAMFORD	234.291262	1780	N	9.485476e+05	5783.070364
5/12	STAMFORD	450.106464	2060	N	1.822293e+06	7021.644833
12/96	RAY BROOK	69.702387	1517	N	2.821959e+05	2663.909932

Creating a Map

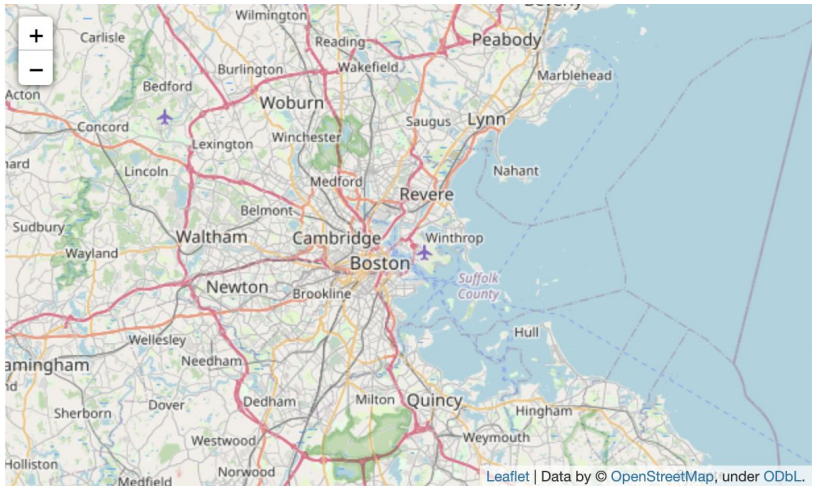



```
# Campsites in New York state (Point)
POI_data = gpd.read_file("../input/geospatial-learn-course-data/DEC_pointsinterest/DEC_pointsinterest/Decptsofinterest.shp")
campsites = POI_data.loc[POI_data.ASSET=='PRIMITIVE CAMPSITE'].copy()

# Foot trails in New York state (LineString)
roads_trails = gpd.read_file("../input/geospatial-learn-course-data/DEC_roadstrails/DEC_roadstrails/Decroadstrails.shp")
trails = roads_trails.loc[roads_trails.ASSET=='FOOT TRAIL'].copy()

# County boundaries in New York state (Polygon)
counties = gpd.read_file("../input/geospatial-learn-course-data/NY_county_boundaries/NY_county_boundaries/NY_county_boundaries.shp")
```

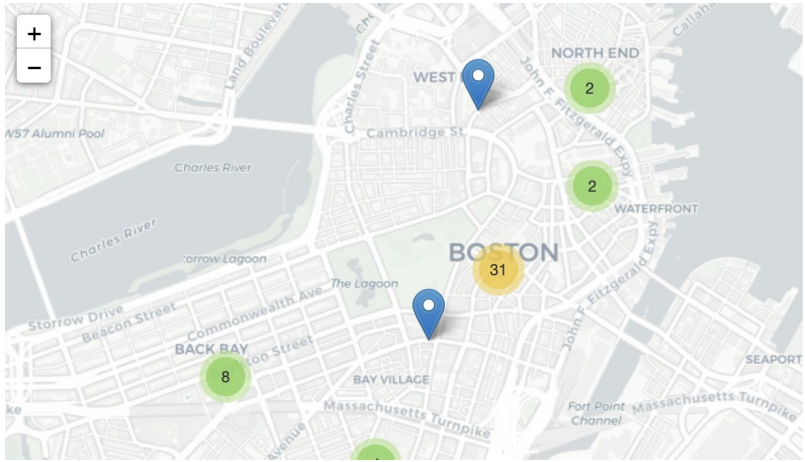


Interactive Maps

```
m_1 = folium.Map(location=[42.32,-71.0589], tiles='openstreetmap', zoom_start=10)
```

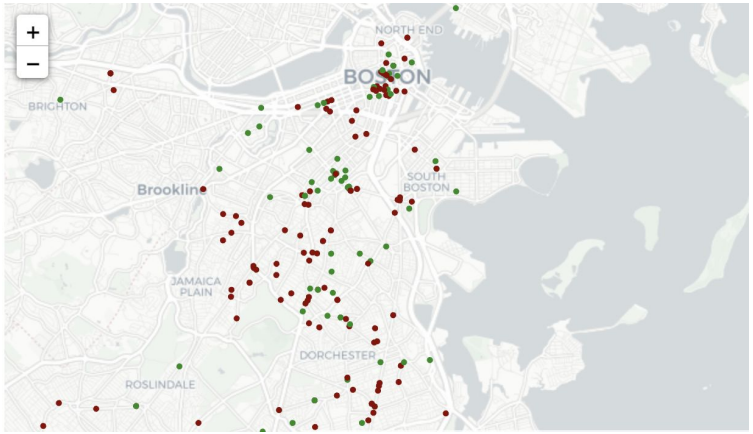



```
m_3 = folium.Map(location=[42.32,-71.0589], tiles='cartodbpositron', zoom_start=13)

# Add points to the map
mc = MarkerCluster()
for idx, row in daytime_robberies.iterrows():
    if not math.isnan(row['Long']) and not math.isnan(row['Lat']):
        mc.add_child(Marker([row['Lat'], row['Long']]))
m_3.add_child(mc)
```

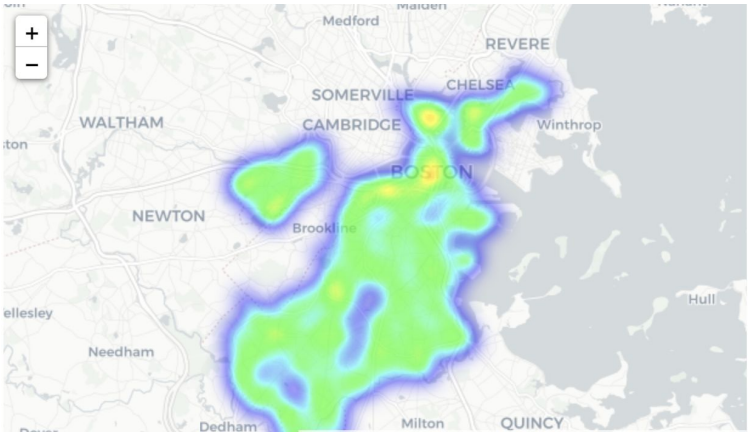


Types of Maps

Bubble Map



Heatmap



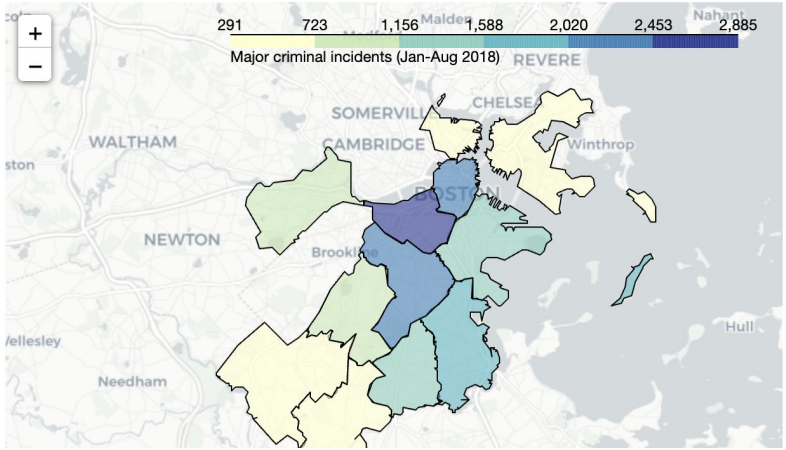
Choropleth Maps

DISTRICT	
A15	MULTIPOLYGON (((-71.07416 42.39051, -71.07415 ...
A7	MULTIPOLYGON (((-70.99644 42.39557, -70.99644 ...
A1	POLYGON ((-71.05200 42.36884, -71.05169 42.368...
C6	POLYGON ((-71.04406 42.35403, -71.04412 42.353...
D4	POLYGON ((-71.07416 42.35724, -71.07359 42.357...

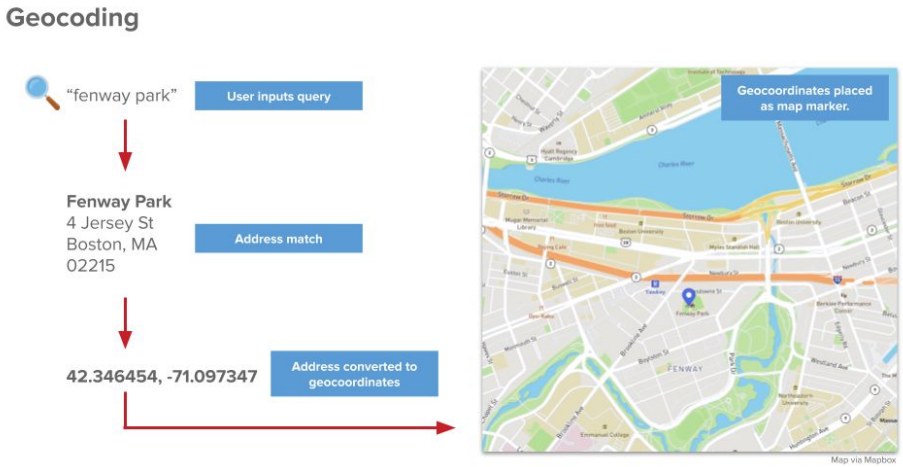
```
plot_dict = crimes.DISTRICT.value_counts()
plot_dict.head()
```

```
D4     2885
B2     2231
A1     2130
C11    1899
B3     1421
Name: DISTRICT, dtype: int64
```

```
m_6 = folium.Map(location=[42.32,-71.0589], tiles='cartodbpositron', zoo
m_start=12)

# Add a choropleth map to the base map
Choropleth(geo_data=districts.__geo_interface__,
           data=plot_dict,
           key_on="feature.id",
           fill_color='YlGnBu',
           legend_name='Major criminal incidents (Jan-Aug 2018)'
          ).add_to(m_6)
```



Manipulating Geospatial Data




```
from geopy.geocoders import Nominatim
```


```
geolocator = Nominatim(user_agent="kaggle_learn")
location = geolocator.geocode("Pyramid of Khufu")

print(location.point)
print(location.address)
```

Latitude:
29.97915995

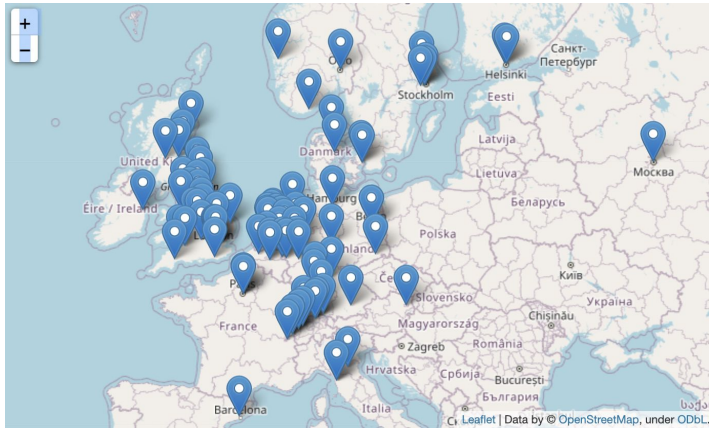
Longitude:
31.134215650388754

Manipulating Geospatial Data

```
universities = pd.read_csv("../input/geospatial-learn-course-data/top_universities.csv")
universities.head()
```

	Name
0	University of Oxford
1	University of Cambridge
2	Imperial College London
3	ETH Zurich
4	UCL

```
def my_geocoder(row):
    try:
        point = geolocator.geocode(row).point
        return pd.Series({'Latitude': point.latitude, 'Longitude': point.longitude})
    except:
        return None

universities[['Latitude', 'Longitude']] = universities.apply(lambda x: my_geocoder(x['Name']), axis=1)

print("{}% of addresses were geocoded!".format(
    (1 - sum(np.isnan(universities["Latitude"])) / len(universities)) * 100))
```



Proximity Analysis

Measuring distance

```
# Select one release incident in particular
recent_release = releases.iloc[360]

# Measure distance from release to each station
distances = stations.geometry.distance(recent_release.geometry)
distances
```

```
print('Closest monitoring station ({} feet):'.format(distances.min()))
print(stations.iloc[distances.idxmin()][["ADDRESS", "LATITUDE", "LONGITUDE"]])
```

```
Closest monitoring station (3780.623590556444 feet):
ADDRESS      3100 Penrose Ferry Road
LATITUDE                   39.91279
LONGITUDE                -75.185448
Name: 9, dtype: object
```

```
print(stations.crs)
print(releases.crs)
```

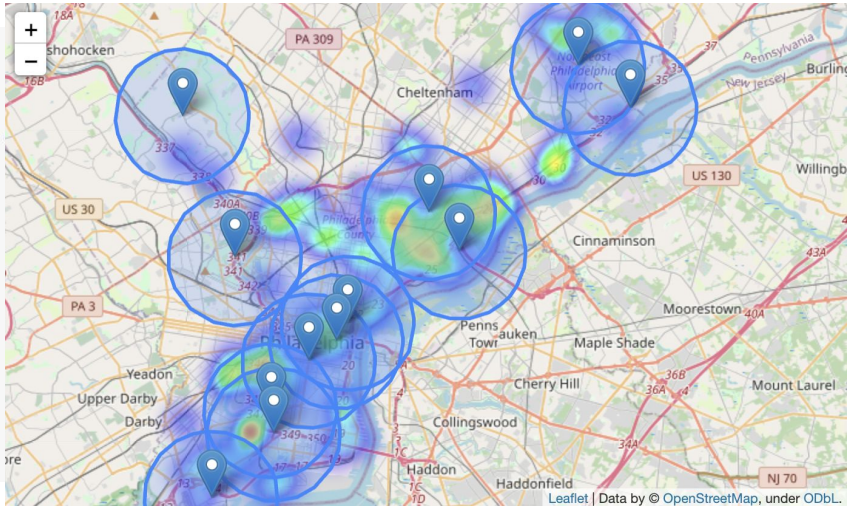
```
epsg:2272
epsg:2272
```

Proximity Analysis

Creating a buffer

```
two_mile_buffer = stations.geometry.buffer(2*5280)
two_mile_buffer.head()
```

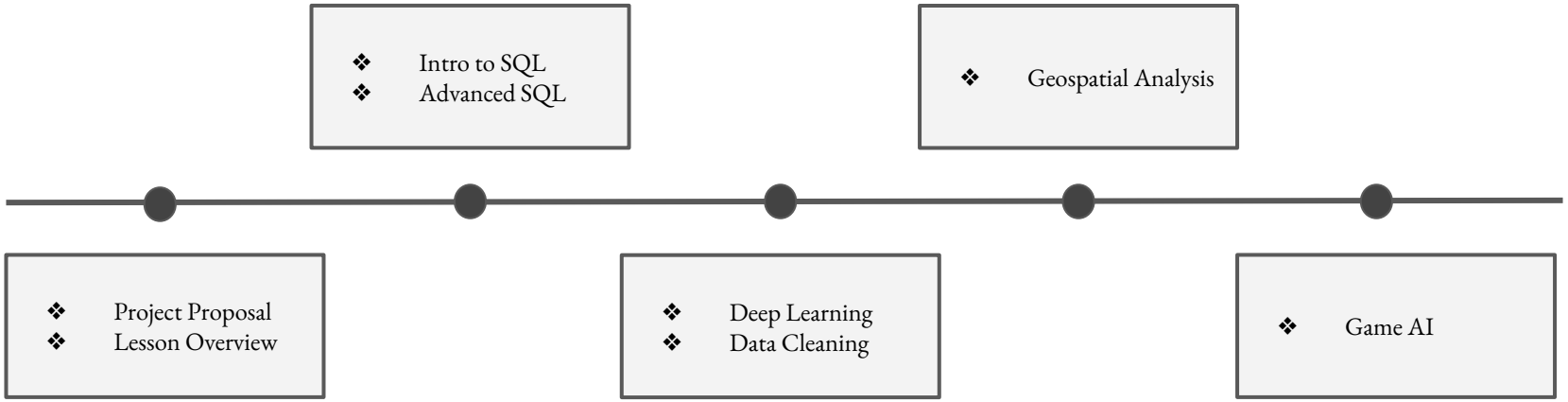
```
# Create map with release incidents and monitoring stations
m = folium.Map(location=[39.9526,-75.1652], zoom_start=11)
HeatMap(data=releases[['LATITUDE', 'LONGITUDE']], radius=15).
for idx, row in stations.iterrows():
    Marker([row['LATITUDE'], row['LONGITUDE']]).add_to(m)

# Plot each polygon on the map
GeoJson(two_mile_buffer.to_crs(epsg=4326)).add_to(m)

# Show the map
m
```



End of Semester Summary

이재욱, 이한나, 이나경, 이태경

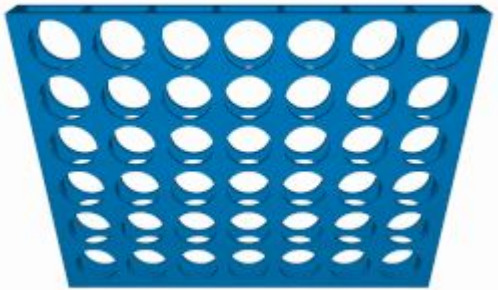
Timeline


❖ Project Proposal
❖ Lesson Overview
❖ Intro to SQL
❖ Advanced SQL
❖ Deep Learning
❖ Data Cleaning
❖ Geospatial Analysis
❖ Game AI

SQL

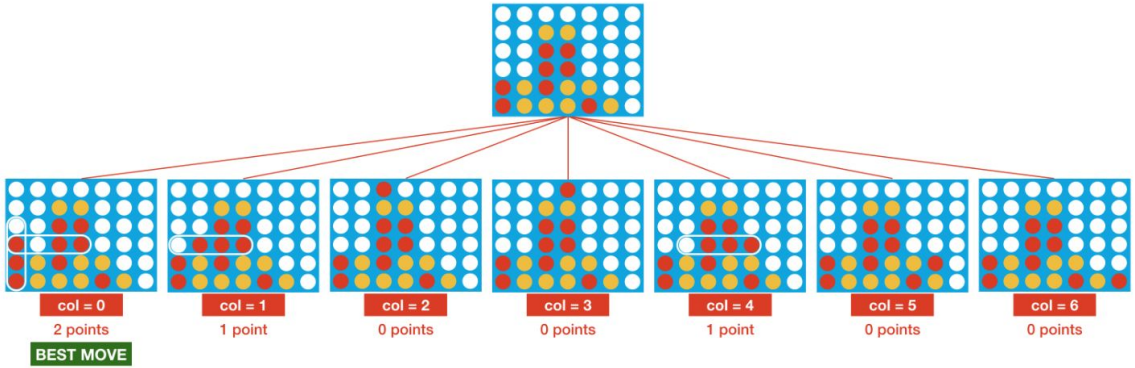
SQL	Python
● Programming language to manage and retrieve data from databases ● Focus is to ‘create’ and ‘maintain’ the datasets ● Access and extract data from database ● Not designed for high level data ● Industry Standard ● Querying data is faster than Python (Simple)	● Analyze and manipulate data ● Specifically designed to create applications

Game AI

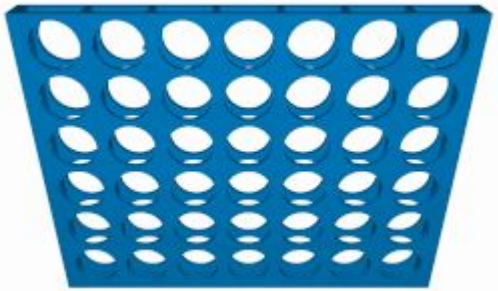


Traditional Method

- Minimax algorithm to dramatically improve your agent
- Use heuristic function
- Agent plans to select move that maximizes score



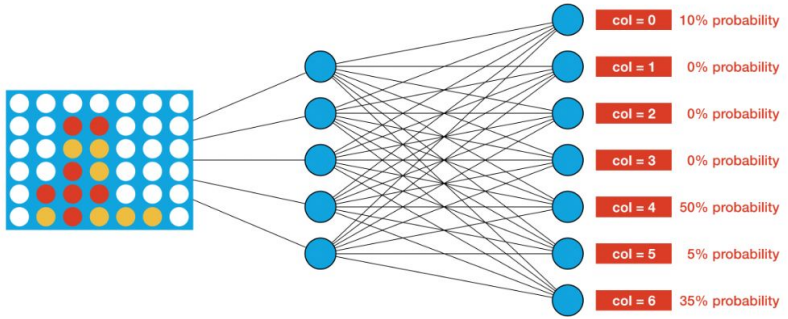
Game AI



```
# Create the game environment
env = make("connectx")

# Two random agents play one game round
env.run([agent1, "random"])

# Show the game
env.render(mode="ipython")
```

Reinforcement Learning

- Advanced techniques for creating intelligent agents
- No heuristic function
- Replace heuristic with neural networks
- Display probability for each possible move

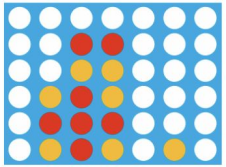


Game AI _ Defining Agents

```
# Selects random valid column
def agent_random(obs, config):
    valid_moves = [col for col in range(config.columns) if obs.board[col] == 0]
    return random.choice(valid_moves)

# Selects middle column
def agent_middle(obs, config):
    return config.columns//2

# Selects leftmost valid column
def agent_leftmost(obs, config):
    valid_moves = [col for col in range(config.columns) if obs.board[col] == 0]
    return valid_moves[0]
```

obs.

- `obs.board` - the game board (a Python list with one item for each grid location)
- `obs.mark` - the piece assigned to the agent (either `1` or `2`)



`obs.board` would be `[0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 2, 2, 0, 0, 0, 0, 2, 1, 2, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 2, 1, 2, 0, 2, 0]`.

config.

- `config.columns` - number of columns in the game board (`7` for Connect Four)
- `config.rows` - number of rows in the game board (`6` for Connect Four)
- `config.inarow` - number of pieces a player needs to get in a row in order to win (`4` for Connect Four)