

CE801 - 7 - Au

Dec 14, 2022

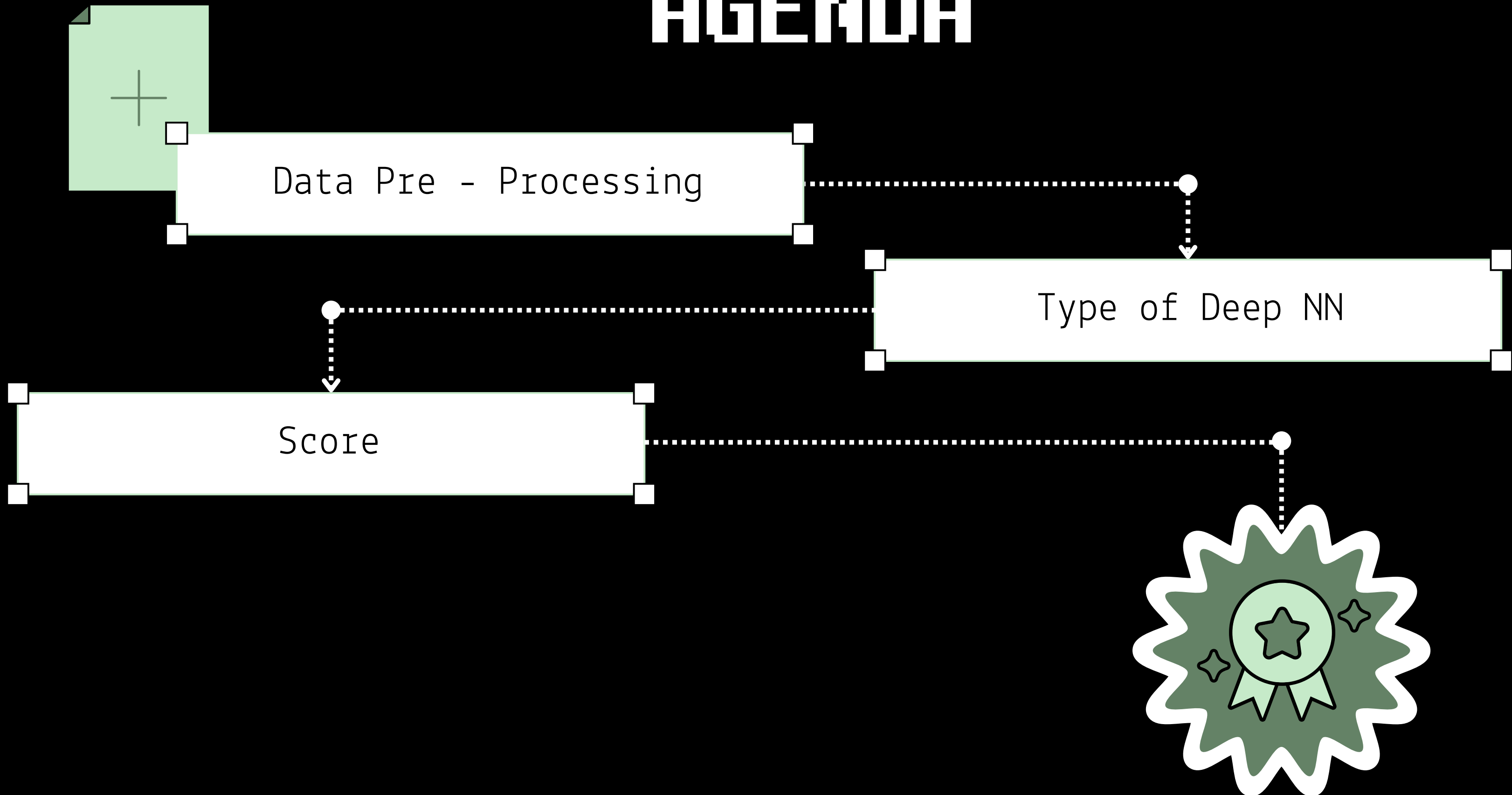
GROUP ASSIGNMENT

GROUP 1

Rossmann Stores sales
Kaggle Competition

Let's get started

AGENDA



DATA

| | A | B | C | D | E | F | G | H | I |
|------|-------|-----------|-----------|-------|-----------|------|-------|--------------|---------------|
| 1 | Store | DayOfWeek | Date | Sales | Customers | Open | Promo | StateHoliday | SchoolHoliday |
| 1109 | 1108 | 5 | 7/31/2015 | 6602 | 645 | 1 | 1 | 0 | 1 |
| 1110 | 1109 | 5 | 7/31/2015 | 5263 | 515 | 1 | 1 | 0 | 0 |
| 1111 | 1110 | 5 | 7/31/2015 | 6198 | 642 | 1 | 1 | 0 | 1 |
| 1112 | 1111 | 5 | 7/31/2015 | 5723 | 422 | 1 | 1 | 0 | 1 |
| 1113 | 1112 | 5 | 7/31/2015 | 9626 | 767 | 1 | 1 | 0 | 1 |
| 1114 | 1113 | 5 | 7/31/2015 | 7289 | 720 | 1 | 1 | 0 | 1 |
| 1115 | 1114 | 5 | 7/31/2015 | 27508 | 3745 | 1 | 1 | 0 | 1 |
| 1116 | 1115 | 5 | 7/31/2015 | 8680 | 538 | 1 | 1 | 0 | 1 |
| 1117 | 1 | 4 | 7/30/2015 | 5020 | 546 | 1 | 1 | 0 | 1 |
| 1118 | 2 | 4 | 7/30/2015 | 5567 | 601 | 1 | 1 | 0 | 1 |
| 1119 | 3 | 4 | 7/30/2015 | 8977 | 823 | 1 | 1 | 0 | 1 |
| 1120 | 4 | 4 | 7/30/2015 | 10387 | 1276 | 1 | 1 | 0 | 1 |
| 1121 | 5 | 4 | 7/30/2015 | 4943 | 539 | 1 | 1 | 0 | 1 |
| 1122 | 6 | 4 | 7/30/2015 | 4790 | 541 | 1 | 1 | 0 | 1 |
| 1123 | 7 | 4 | 7/30/2015 | 11560 | 1116 | 1 | 1 | 0 | 1 |
| 1124 | 8 | 4 | 7/30/2015 | 8420 | 882 | 1 | 1 | 0 | 1 |
| 1125 | 9 | 4 | 7/30/2015 | 7539 | 651 | 1 | 1 | 0 | 1 |
| 1126 | 10 | 4 | 7/30/2015 | 6186 | 556 | 1 | 1 | 0 | 1 |
| 1127 | 11 | 4 | 7/30/2015 | 7361 | 874 | 1 | 1 | 0 | 1 |

ARRANGEMENT OF THE DATA

The table of data shows that the arrangement of data is arranged as sequential data

As the data is arranged as sequential so we are looking for a model that good for the processing sequential data prediction

Data Preprocessing steps

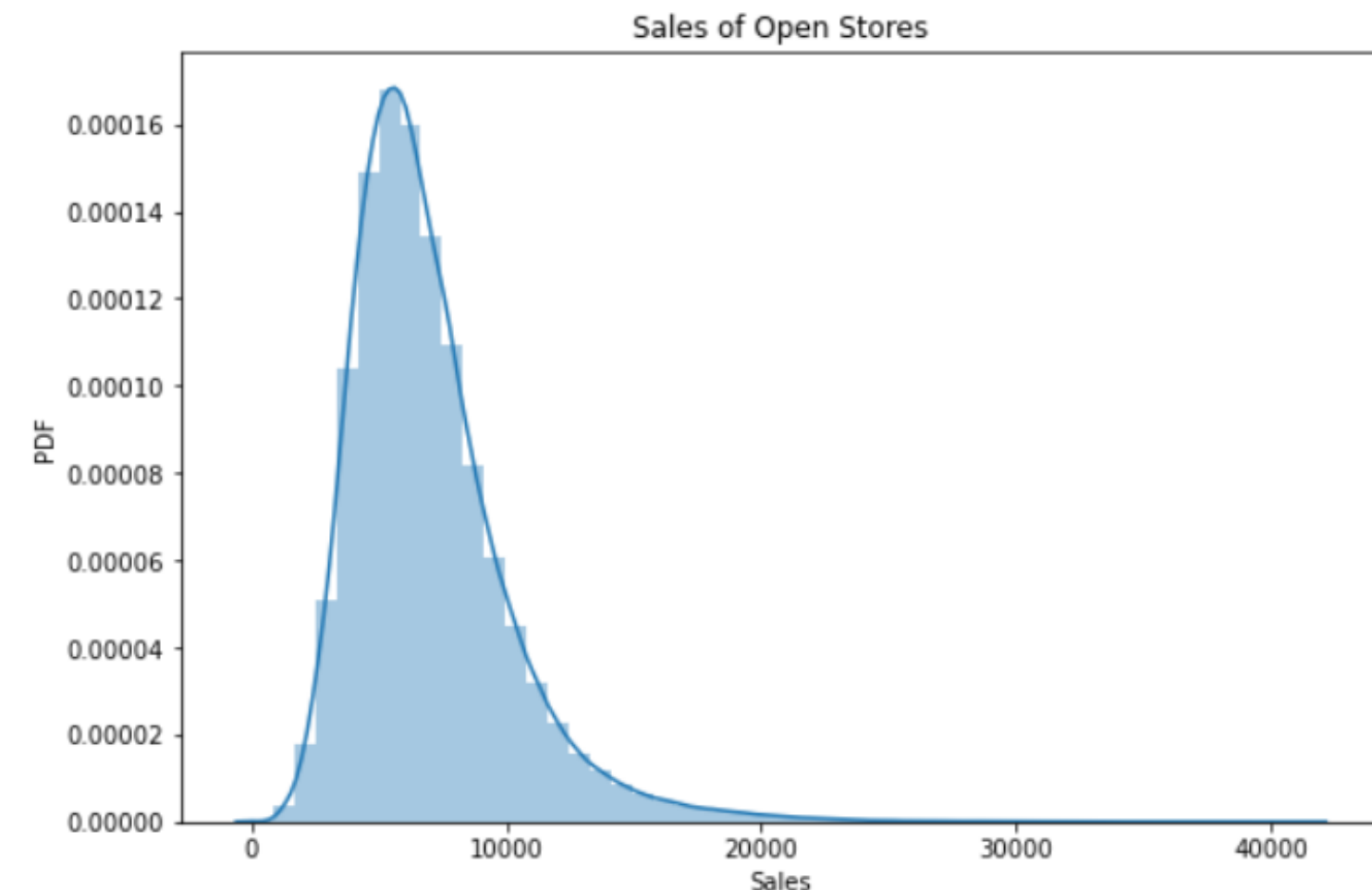
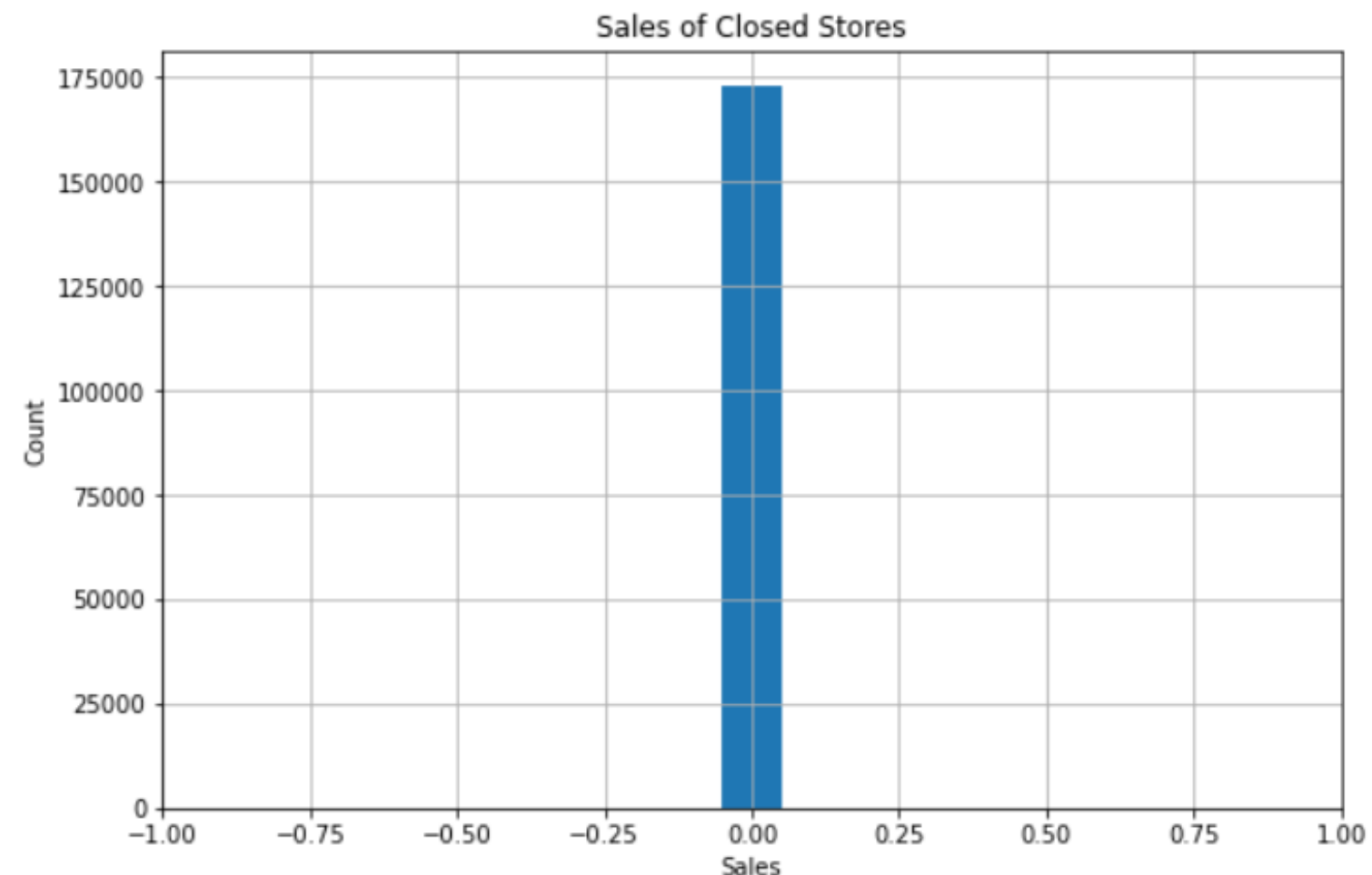


- **Import `missingno` as `msno`:** The `msno.matrix` nullity matrix is a data-dense display which lets you quickly visually pick out patterns in data completion
- **Import `seaborn` as `sns`:** Seaborn is a library that uses Matplotlib underneath to plot graphs. It will be used to visualize random distributions.
- **from `sklearn.impute` import `SimpleImputer`:** “most_frequent”, then replace missing using the most frequent value along each column.
- **from `time` import `time`:** The `time()` function returns the number of seconds passed since epoch.
- **from `keras.models` import `Sequential`**
- **from `keras.layers` import `Dense`**
- **from `keras.layers` import `LSTM`**
- **from `keras.layers` import `Dropout`**
- **import `tensorflow` as `tf`**

Stages of Pre processing

- Display all columns that contain null values in all files
- We plot a histogram of sales for days when shops are closed to know distribution
- We used `distplot()` function to represents data distribution of a sales of open shop against the density distribution.
- Then we calculate the skewness of sales about its mean

The skewness of Sales is 1.5939220392699809



Stages of Pre processing

- Visualize the missing values in store



Dealing with missing values

- **test.fillna(1,inplace=True):** Fill missing values with 1
- **store.CompetitionDistance=store.CompetitionDistance.fillna(store.CompetitionDistance.median())=** Fill competition distance in store with median values because SD is more than the mean
- **store.fillna(0,inplace=True):** Impute missing values to zero replace the missing values using the most frequent value along each column
- Mapped the categorial values into numbers
- **StoreType**
- **Assortment**
- **StateHoliday**
- Visualize the relation between variables using heatmap strength of the correlation

Stages of Pre processing

- We Extract features from Date column to years month for easy filtering
- `data['CompetitionOpen'] = 12*(data.Year - data.CompetitionOpenSinceYear) + (data.Month - data.CompetitionOpenSinceMonth)`
- We Convert data type of Date column: from Object => datetime and then extract features from Date, for easy filtering.

DATA

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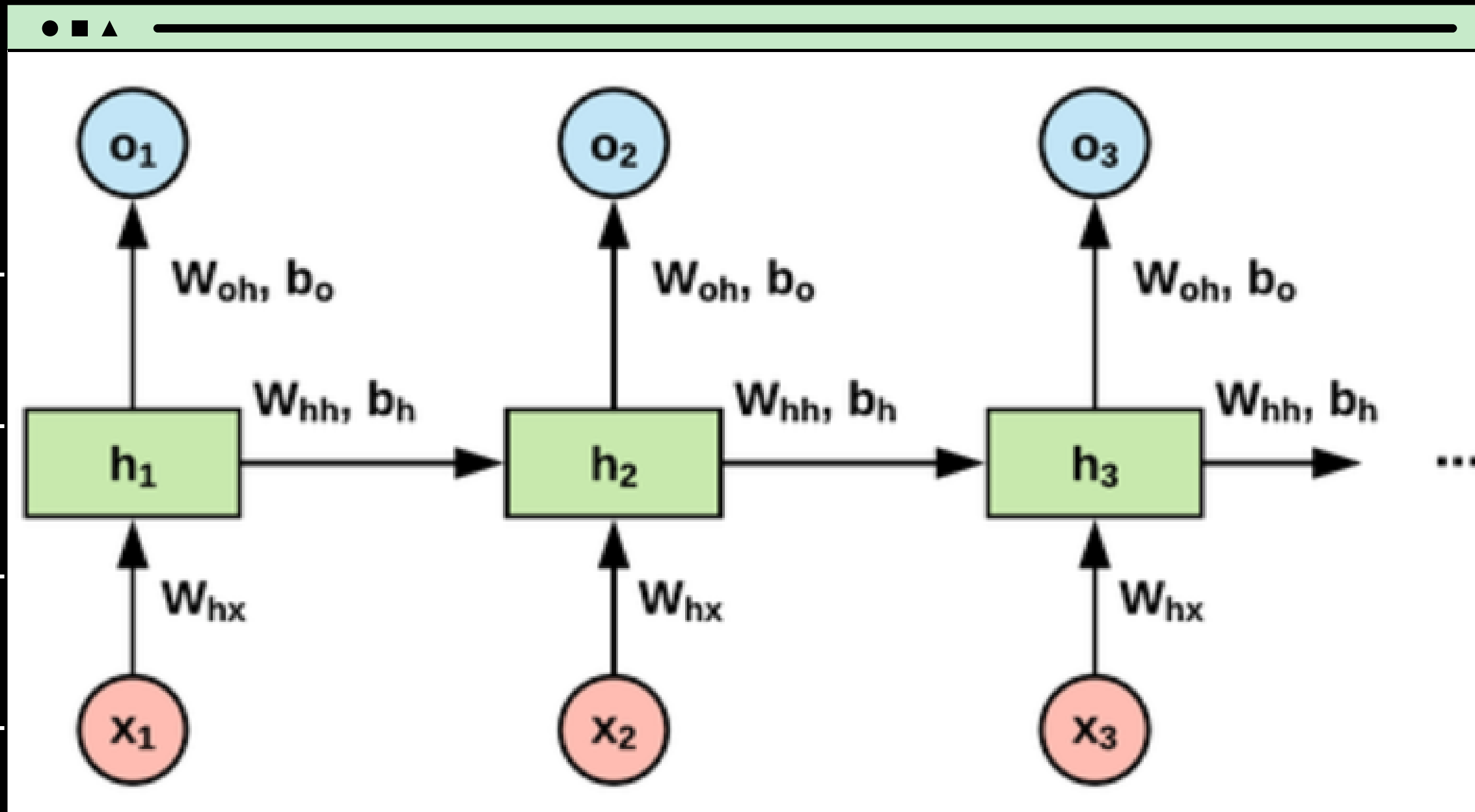
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RNN MODEL

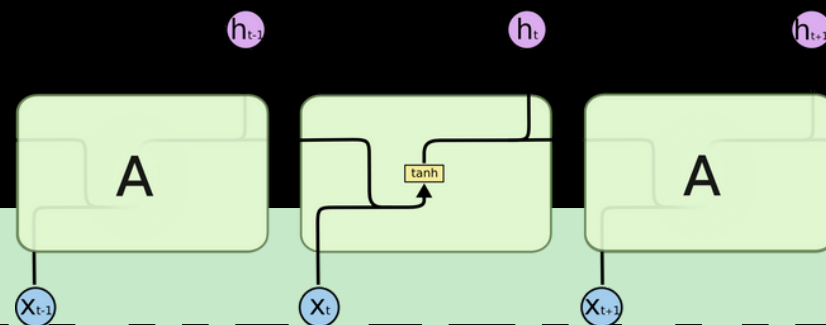
WHY RNN



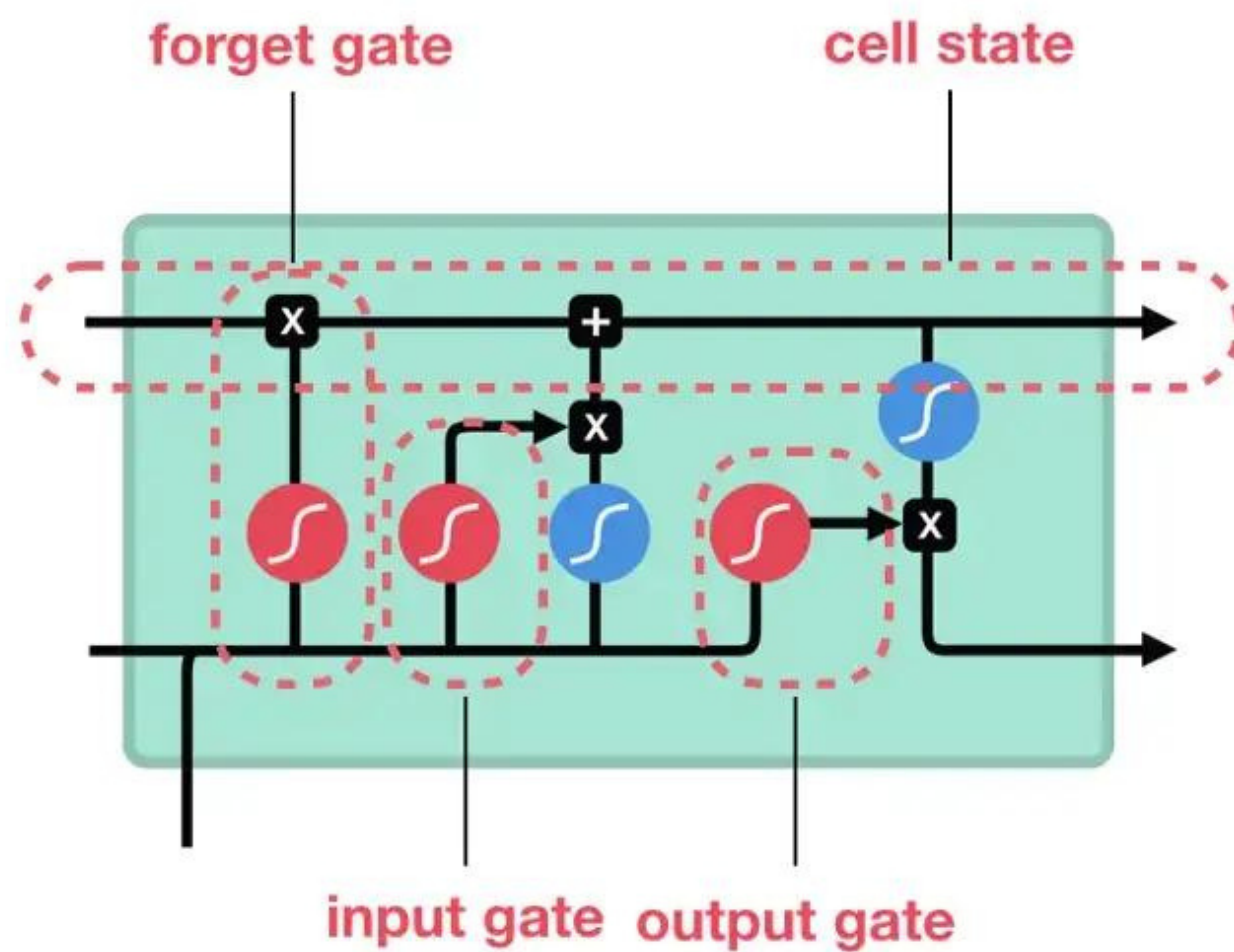
- RNN Models are good for processing **sequential data** prediction
- Data that are good for using RNN Models such as Audio, Text, **Stock Price** or any time-series data



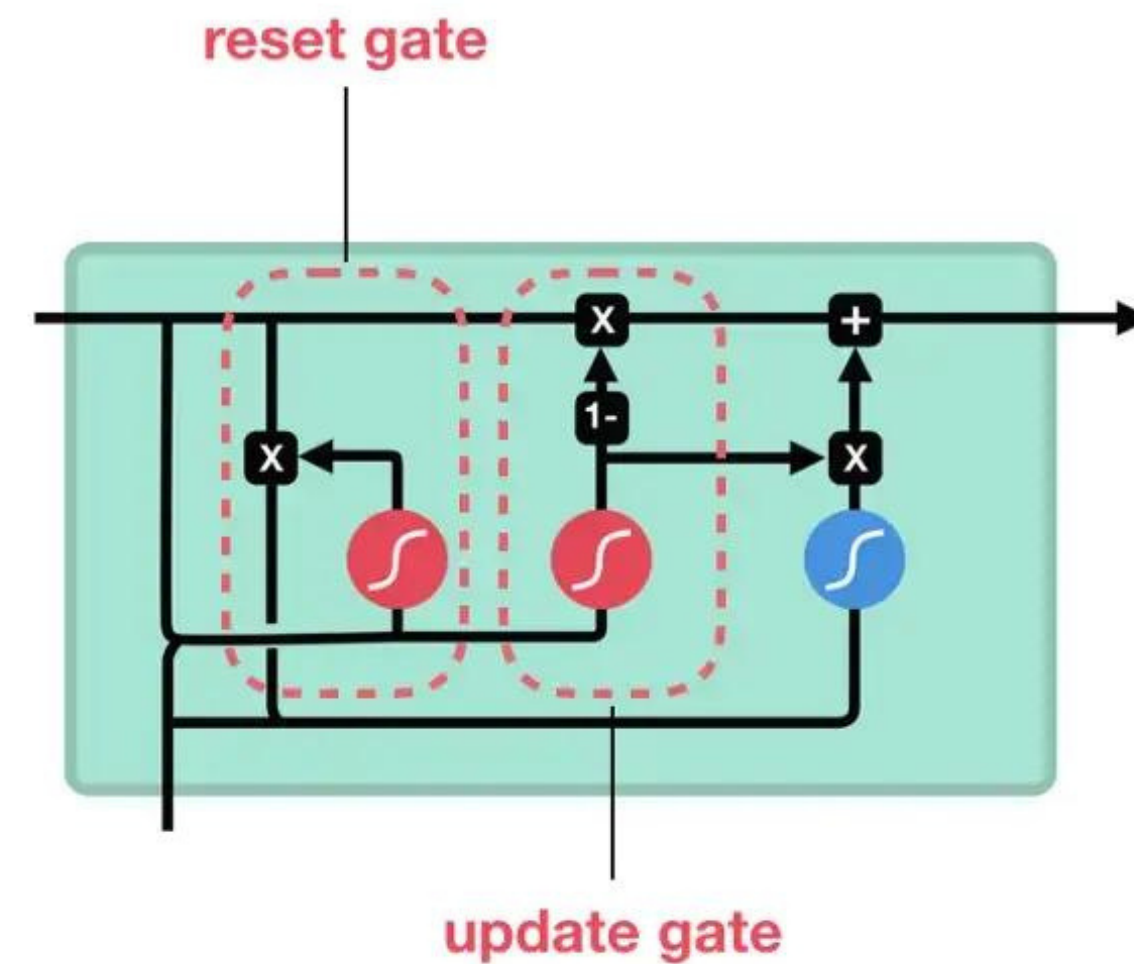
LSTM VS GRU MODEL



LSTM

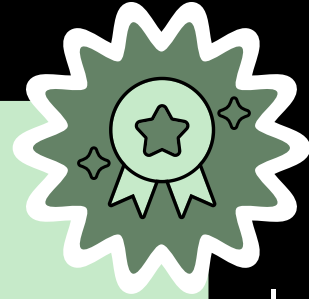


GRU



MODEL COMPARISON

LSTM



GRU

GRU

- less training parameter and therefore uses less memory
- executes faster than LSTM

LSTM

- more accurate on a larger dataset.

```
lookback = 14 # The lookback is the number of days we want our model to use before the starting dates to use as a
# In these for loops we append the test and train tests. This is to create the new arrays that will train the model.
# They start in train because of the lookback and in each for moves to the right until they reach the test set and e
# start only predicting on the test set itself
data_new = []

for i in range(1115):
    data_new.append(xtrain[xtrain['Store']==1+i].values)
x_train_new_2, y_train_new_2 = [], []
for i in range(len(data_new)):
    for j in range(data_new[i].shape[0]-lookback-1):
        x_train_new_2.append(data_new[i][j:j+lookback])
        y_train_new_2.append(data_new[i][j+lookback+1,2])
# x_train.append(np.array(x_train_new_2))
# y_train.append(np.array(y_train_new_2))
x_train_new_2 = np.array(x_train_new_2)
y_train_new_2 = np.array(y_train_new_2)
```

**USE TRAIN AND TEST
SET FOR ONE
PREDICTION**

NETWORK ARCHITECTURE

LSTM

- 1 hidden layer consisting of 50 units with 10 percent dropout
- 2 hidden layers with 50 units each, following a 20 percent dropout
- 2 dense layers, consisting of 8 and 1 unit respectively.
- Adam is the optimizer and MSE is the loss function and target

FILL DATES AND INFERENCE BASED ON DATES AND STORES

*#This was used as an autoregressive model. This is where we do the inference of the model after it has been trained.
First we had to fill the missing values for dates. And after that, using the date and store we could infer the sales
store in the future.*

```
total_data = total_data.sort_values(by=['Store', 'Year', 'Month', 'Day'])

test_inputs = []
for row in reversed(xtest.values):
    store_id = row[0]
    year, month, day = int(row[15]), int(row[16]), int(row[17])
    print(year, month, day)
    date = take_to_datetime(year, month, day)
    ret = []
    for i in range(lookback):
        new_date = date - datetime.timedelta(days=lookback-i)
        new_year, new_month, new_day = return_from_datetime(new_date)
        if (total_data[(total_data['Store'] == store_id) & (total_data['Year'] == new_year) & (total_data['Month'] == new_month) & (total_data['Day'] == new_day)]).empty:
            ret.append(total_data[(total_data['Store'] == store_id) & (total_data['Year'] == new_year) & (total_data['Month'] == new_month) & (total_data['Day'] == new_day)])
        else:
            temp = np.zeros((1, 22))
            temp[0,0], temp[0,14], temp[0,15], temp[0,16] = store_id, new_year, new_month, new_day
            ret.append(temp)
    sales_pred = train_model.predict(np.array(ret).reshape(1, 14, 22))
    total_data.loc[(total_data['Store'] == store_id) & (total_data['Year'] == year) & (total_data['Month'] == month) & (total_data['Day'] == day)] = sales_pred
    xtest.loc[(xtest['Store'] == store_id) & (xtest['Year'] == year) & (xtest['Month'] == month) & (xtest['Day'] == day)] = sales_pred
```

SCORE



Submissions


You selected 0 of 2 submissions to be evaluated for your final leaderboard score. Since you selected less than 2 submission, Kaggle auto-selected up to 2 submissions from among your public best-scoring unselected submissions for evaluation. The evaluated submission with the best Private Score is used for your final score.

0/2

☐ Submissions evaluated for final score

- All
- Successful
- Selected
- Errors

Recent

| Submission and Description | | Private Score ⓘ | Public Score ⓘ | Selected |
|---|---------------------------------|-----------------|----------------|--------------------------|
|  | good_Submission.csv | 0.5503 | 0.49775 | <input type="checkbox"/> |
| | Complete (after deadline) · now | | | |

MEMBERS



MODEL BUILDING AND RUNNING

Zepeda Aguirre
Raul

2204398

Ali
Syed Asad

2207947

DATA PREPARATION

Agarwal
Ishita

2201110

Chaudhary
Muhammad Umer

0000000

MODEL SELECTION

Pratjaroenwanit
Thanaphoom

2209324

Tochayamanon
Nontanat

2209337

References

https://www.w3schools.com/python/numpy/numpy_random_seaborn.asp