

# Forecasting Future Walmart Sales using KNN Regression

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## Introduction

- Walmart Data set imported from Kaggle
- Comprised of three main CSV files containing correlation of different features, based on data pulled from 45 different store locations, with a number of departments in each store
- Features vary from numerical values, such as amount of sales, to boolean True/False for if a week contains a holiday or not
- Goal is to build/train a model that can predict future Walmart sales based on a specific store/department and date



Figure 1: Sample Walmart Store

## Dataset

- Relevant CSVs within the dataset are listed below, along with the features within each one
- features.csv*: Store #, Date, Local Temperature, Local Fuel Price, Markdown/Discounts, CPI index, Unemployment Index, and if the current week is a holiday
- stores.csv*: Store#, Type of Store, and size of store by number of products
- train.csv*: Store#, Department#, Date, Weekly Sales, and if the current week is a holiday

Store	Dept	Date	Weekly_Sales	IsHoliday	Store	Type	Size	Store	Date	Temperature	Fuel_Price	Mar_Mark	Mar_Mark	CPI	Unemployment	IsHoliday			
1	1	1/2/2010	24924.5	FALSE	2	1	A	151315	2	1	A	2.572	NA	NA	NA	211	8.106	FALSE	
3	1	1	46039.49	TRUE	3	2	A	202307	3	1	A	38.51	2.548	NA	NA	NA	211	8.106	TRUE
4	1	1	41595.55	FALSE	4	3	B	37392	4	1	A	39.99	2.514	NA	NA	NA	211	8.106	FALSE
5	1	1	19403.54	FALSE	5	4	A	205863	5	1	A	46.63	2.561	NA	NA	NA	211	8.106	FALSE
6	1	1/5/2010	21827.9	FALSE	6	5	B	34875	6	1	A	46.5	2.625	NA	NA	NA	211	8.106	FALSE
7	1	1	20454.39	FALSE	7	6	A	202295	7	1	A	57.79	2.667	NA	NA	NA	211	8.106	FALSE
8	1	1	22136.64	FALSE	8	7	B	70713	8	1	A	54.58	2.72	NA	NA	NA	211	8.106	FALSE
9	1	1	26229.21	FALSE	9	8	A	155078	9	1	A	51.45	2.732	NA	NA	NA	211	8.106	FALSE
10	1	1/2/2010	37258.43	FALSE	10	9	B	125833	10	1	A	62.27	2.719	NA	NA	NA	211	7.808	FALSE
11	1	1/4/2010	42960.91	FALSE	11	10	B	126512	11	1	A	65.86	2.77	NA	NA	NA	211	7.808	FALSE
12	1	1	17596.96	FALSE	12	11	A	207499	12	1	A	66.32	2.808	NA	NA	NA	210	7.808	FALSE
13	1	1	16145.35	FALSE	13	12	B	112238	13	1	A	64.84	2.795	NA	NA	NA	210	7.808	FALSE
14	1	1	16555.11	FALSE	14	13	A	219622	14	1	A	67.41	2.78	NA	NA	NA	210	7.808	FALSE
15	1	1/7/2010	17413.94	FALSE	15	14	A	200898	15	1	A	72.55	2.835	NA	NA	NA	210	7.808	FALSE
16	1	1/6/2010	18926.74	FALSE	16	15	B	123737	16	1	A	74.78	2.854	NA	NA	NA	210	7.808	FALSE
17	1	1	14773.04	FALSE	17	16	B	57197	17	1	A	76.44	2.826	NA	NA	NA	211	7.808	FALSE
18	1	1	15580.43	FALSE	18	17	B	93188	18	1	A	80.44	2.759	NA	NA	NA	211	7.808	FALSE
19	1	1/6/2010	17558.09	FALSE	19	18	B	126063	19	1	A	80.69	2.705	NA	NA	NA	211	7.808	FALSE
20	1	1	16637.62	FALSE	20	19	A	203819	20	1	A	80.43	2.668	NA	NA	NA	211	7.808	FALSE
21	1	1	16216.27	FALSE	21	20	A	203742	21	1	A	84.11	2.637	NA	NA	NA	211	7.808	FALSE
22	1	1	16326.72	FALSE	22	21	B	140167	22	1	A	84.34	2.653	NA	NA	NA	211	7.808	FALSE
23	1	1/7/2010	16333.14	FALSE	23	22	B	119557	23	1	A	80.91	2.669	NA	NA	NA	211	7.787	FALSE
24	1	1/9/2010	17688.76	FALSE	24	23	B	114533	24	1	A	80.48	2.642	NA	NA	NA	211	7.787	FALSE
25	1	1	17152.84	FALSE	25	24	A	203819	25	1	A	83.15	2.623	NA	NA	NA	211	7.787	FALSE
26	1	1	15360.45	FALSE	26	25	B	128107	26	1	A	83.36	2.608	NA	NA	NA	211	7.787	FALSE
27	1	1	15381.82	FALSE	27	26	A	152513	27	1	A	81.84	2.64	NA	NA	NA	211	7.787	FALSE
28	1	1/6/2010	17558.41	FALSE	28	27	A	204184	28	1	A	87.16	2.627	NA	NA	NA	212	7.787	FALSE
29	1	1	15536.4	FALSE	29	28	A	206302	29	1	A	87	2.692	NA	NA	NA	212	7.787	FALSE
30	1	1	15740.13	FALSE	30	29	B	93638	30	1	A	86.65	2.664	NA	NA	NA	212	7.787	FALSE
31	1	1	15793.87	FALSE	31	30	C	4298	31	1	A	85.22	2.616	NA	NA	NA	212	7.787	FALSE
32	1	1/3/2010	16241.78	FALSE	32	31	A	203750	32	1	A	81.21	2.577	NA	NA	NA	211	7.787	FALSE
33	1	1	18154.74	TRUE	33	32	A	203007	33	1	A	78.69	2.565	NA	NA	NA	211	7.787	TRUE
34	1	1	19354.23	FALSE	34	33	A	39690	34	1	A	82.11	2.582	NA	NA	NA	212	7.787	FALSE
35	1	1	18122.52	FALSE	35	34	A	158114	35	1	A	80.94	2.624	NA	NA	NA	212	7.787	FALSE
36	1	1	20094.19	FALSE	36	35	B	103651	36	1	A	71.89	2.603	NA	NA	NA	212	7.838	FALSE
37	1	1	13384.03	FALSE	37	36	A	39910	37	1	A	69.66	2.631	NA	NA	NA	212	7.838	FALSE
38	1	1	26978.34	FALSE	38	37	C	39910	38	1	A	67.18	2.72	NA	NA	NA	212	7.838	FALSE
39	1	1	25543.04	FALSE	39	38	C	39690	39	1	A	69.66	2.725	NA	NA	NA	212	7.838	FALSE
40	1	1	18640.93	FALSE	40	39	A	184309	40	1	A	69.64	2.716	NA	NA	NA	212	7.838	FALSE
41	1	1	34238.88	FALSE	41	40	A	155083	41	1	A	58.74	2.689	NA	NA	NA	212	7.838	FALSE
42	1	1	19549.39	FALSE	42	41	A	196321	42	1	A	59.61	2.728	NA	NA	NA	212	7.838	FALSE

Figure 2: Snapshot of Three CSV files, Train, Stores, Features (Left to Right)

## Methodology

### Data Cleaning

- Once data was imported using Excel, all following data analysis was done using Python
- The first step was to load the data using the Pandas package, and import the CSV table as a data frame
- We proceeded to remove N/A data, as can be seen in the CSV screenshots in the Dataset section
- Once completed, all three data frames were merged into one, named main
- The main data frame was created by merging on common features between the three data frames, such as Store# and Date

```
#Load all excel files in through pandas
train = pandas.read_csv("train.csv")
features = pandas.read_csv("features.csv")
stores = pandas.read_csv("stores.csv")

#Some values maybe NA depending on stores
#Clean up data

#For unavaialble markdowns, fill with 0
features['Markdown1'] = features["MarkDown1"].fillna(0)
features['Markdown2'] = features["MarkDown2"].fillna(0)
features['Markdown3'] = features["MarkDown3"].fillna(0)
features['Markdown4'] = features["MarkDown4"].fillna(0)
features['Markdown5'] = features["MarkDown5"].fillna(0)
```

Figure 3: Code to Load CSV and Clean Data

### Data Exploration

- The next step was to explore the data and observe strong correlation between features
- The three sets that were observed were: Type of Store vs. Weekly Sales, Type of Store vs. Size of Store, Is Holiday vs. Weekly Sales

### Observations

- Type of Store vs. Weekly Sales: Weak correlation, Type C seems to have least amount of sales, no strong difference between A and B
- Type of Store vs. Size of Store: Strong Correlation, A is largest, B is second largest, C is smallest
- Is Holiday vs. Weekly Sales: Some correlation, with slightly more sales when there was a holiday, however not as much as expected



Figure 4: Type of Store vs. Size of Store

### Data Modelling

- In order to model the data, a machine learning model is normally selected
- We will select the K Nearest Neighbors Regression model
- Regression models allow a solid value to be predicted based on a series of dependent variables, such as we have in our case, since we are predicting future sales per store and department at certain dates
- The KNN approach will allow features to be classified based on their similarities as described with input data. Hence, predicted values will be classified based on how much their data resembles points in the dataset
- This modelling can be done in python using scikit-learn library in Python
- Yet to be finalized*

## Results

- No final results currently yielded*
- Mention if trained model is successful*

## Conclusion

- Concluding remarks*
- Explain how this model could help predict and forecast future sales for department stores*

## References

[1] Kaggle.com, 2014, Walmart Recruiting - Store Sales Forecasting | Kaggle. [online] Available at: <https://www.kaggle.com/c/walmart-recruiting-store-sales-forecasting/data> [Accessed 31 January 2021].

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