Deep Learning Applications in Supply Chain Management

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Agenda

1. Results
2. Supply Chain Management Overview
3. Research Objective
4. Data Overview
5. Methodology
6. Wrap Up

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Results

LSTM Results

Training/Validation

- Validation **MSE**: **0.0025**
- Validation **MAPE: 21.66**
  - ➔ greater than 78% accurate!

Testing

- Average **Accuracy: 0.968**

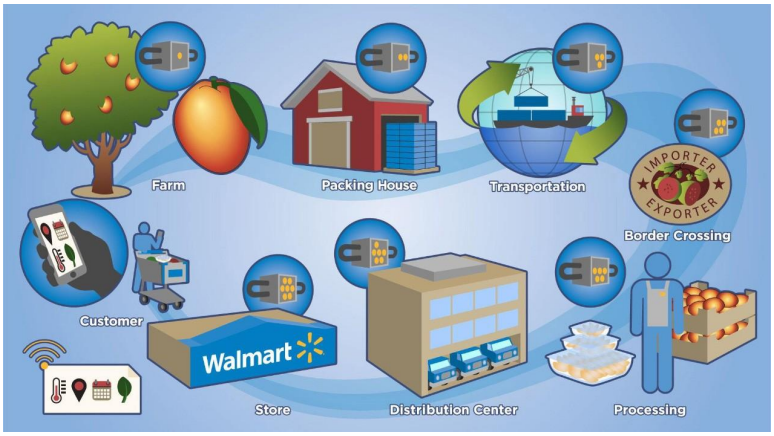
Supply Chain Management

Supply Chain Management

- **Supply Chain -** the complete process for delivery of a consumer good from product order placement to arrival to consumers (Lin et al., 2022)

- **Supply Chain Management -** the active management of the following constituent processes: demand (sales) estimation, raw material purchasing, supplier selection, production, product distribution, outbound transportation, and inventory management (Aamer et al., 2020; Lin et al., 2022; Tirkolaee et al., 2021)

Example Supply Chain



% Wall Street Journal | Walmart

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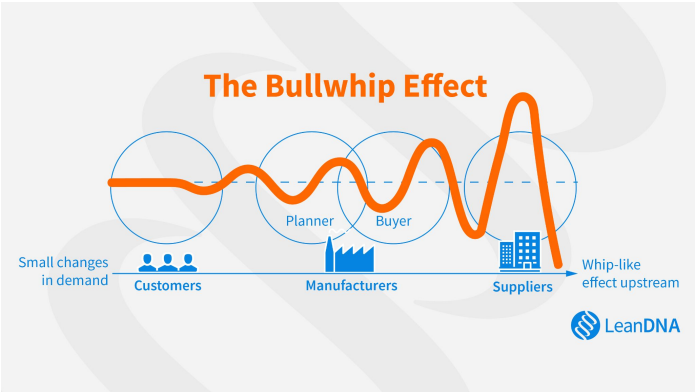
Demand forecasting aims to ameliorate the Bullwhip Effect



% Lean DNA

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Research Objective

Research Objective

Train a neural network that predicts consumer demand with at least 70% accuracy

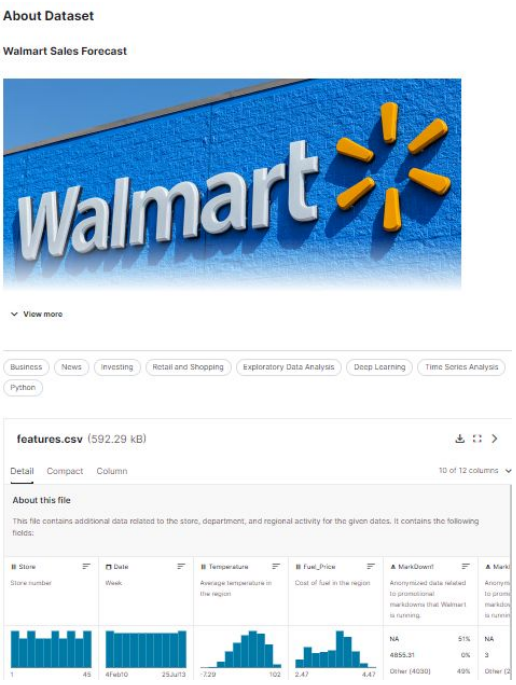
(based on accepted commercial forecasting standards (Skarica, 2022))

Could support literature claim that ANNs are the most accurate SCM forecasting methods

Data Overview

Walmart Data

- Retrieved from Kaggle
- Walmart US Sales data from 2010-2012
- ~13 MB (412,000 obs)
    - Reduced to 143 observations after data aggregation
- Response variable: **weekly sales**
- Features:
    - **date**
    - unemployment rate
    - inflation
    - holiday
    - fuel price
    - temperature
- only date was retained



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Observed Demand

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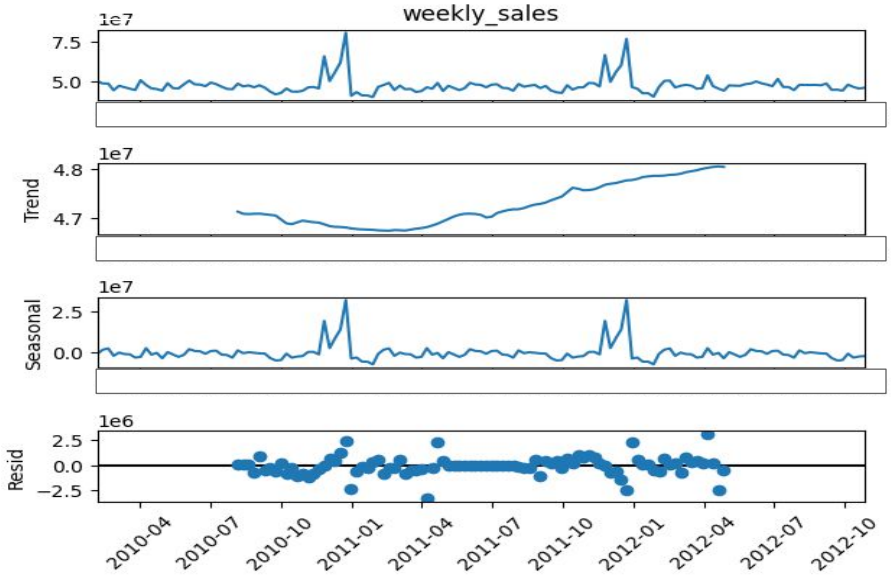
Deeper Demand Trends



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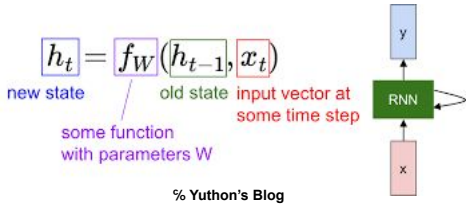
Methodology

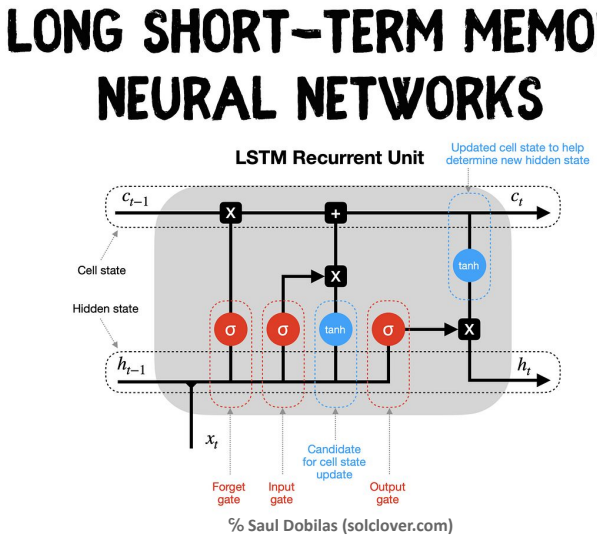
Recurrent Neural Network

- Most used NN architecture for time series analysis



% Yuthon's Blog

LSTM General Architecture



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Model Details

- 2 hidden layers
- 5,061 parameters
- Optimizer: ADAM
- Learning Rate: 0.001
- Loss Function: MSE
- Key Metrics: MAPE

lstm_29_input	input:	[(None, None, 1)]
InputLayer	output:	[(None, None, 1)]

lstm_29		input:	(None, None, 1)
LSTM	tanh	output:	(None, None, 20)

lstm_30		input:	(None, None, 20)
LSTM	tanh	output:	(None, None, 20)

dense_11		input:	(None, None, 20)
Dense	linear	output:	(None, None, 1)

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Model Construction Code

Design and Train LSTM Network

```
[ ]  1 from keras.models import Sequential
     2 from keras.layers import LSTM
     3 from keras.layers import Dense
```

```
[ ]  1 from keras import callbacks
     2 earlystopping = callbacks.EarlyStopping(monitor="val_loss",
     3                                         mode="min", patience=5,
     4                                         restore_best_weights=True)
     5 model = keras.models.Sequential([
     6     keras.layers.LSTM(int(20), return_sequences=True, input_shape=[None, 1]),
     7     keras.layers.LSTM(int(20), return_sequences=True),
     8     keras.layers.Dense(int(1))
     9 ])
    10
    11 model.compile(loss="mse", optimizer="adam", metrics=[tf.keras.metrics.MeanAbsolutePercentageError()])
```

```
[ ]  1 # from ann_visualizer.visualize import ann_viz
     2 # from graphviz import Source
     3 # ann_viz(model,view=True)
```

```
[ ]  1 model.summary()
```

```
Model: "sequential_19"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_29 (LSTM)              (None, None, 20)          1760

 lstm_30 (LSTM)              (None, None, 20)          3280

 dense_11 (Dense)            (None, None, 1)           21

=================================================================
Total params: 5,061
Trainable params: 5,061
Non-trainable params: 0
```

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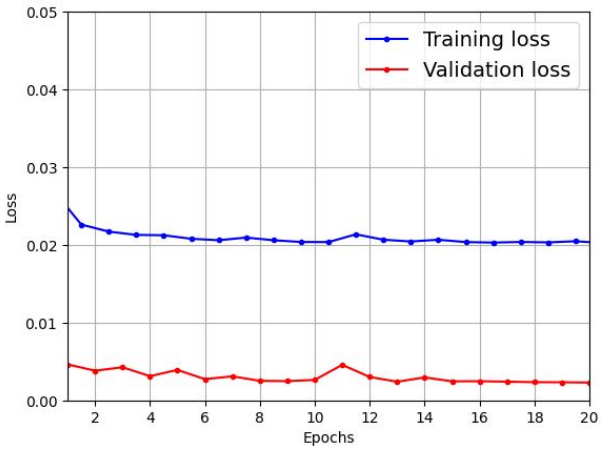
Training

```
history = model.fit(generator, epochs=50,
                    validation_data=valid_gen,
                    callbacks=[earlystopping])
```

- Validation MSE: 0.0025
- Validation MAPE: 21.66
  - ➔ greater than 78% accurate!



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Predictive Accuracy

- Holdout data: last 12 weeks of sales
- **Average Accuracy: 0.968**

date	weekly_sales	Predictions	Accuracy
2012-08-10	47403451.04	45439380.0	0.959
2012-08-17	47354452.05	45439728.0	0.960
2012-08-24	47447323.60	45439064.0	0.958
2012-08-31	47159639.43	45441128.0	0.964
2012-09-07	48330059.31	45432740.0	0.940
2012-09-14	44226038.65	45462332.0	0.972
2012-09-21	44354547.11	45461396.0	0.975
2012-09-28	43734899.40	45465904.0	0.960
2012-10-05	47566639.31	45438208.0	0.955
2012-10-12	46128514.25	45448556.0	0.985
2012-10-19	45122410.57	45455828.0	0.993
2012-10-26	45544116.29	45452776.0	0.998

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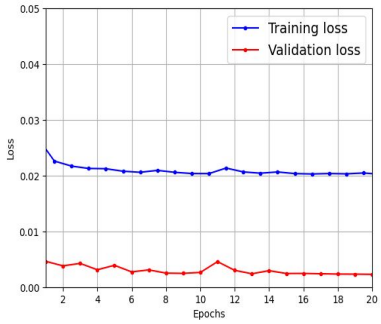
Wrap Up

Recap of Results

- Validation MSE: 0.0025
- Validation MAPE: 21.66
- **Avg. Test Accuracy: 0.968**



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Conclusions

- This analysis offered further evidence of why DL is preferred ML method in SCM
  - DL was used in 49% of SCM forecasting (Aamer et al., 2021)
- Neural Networks offer major advantages to other Machine Learning methods
- ANNs should be preferred in Supply Chain Management and other commercial applications

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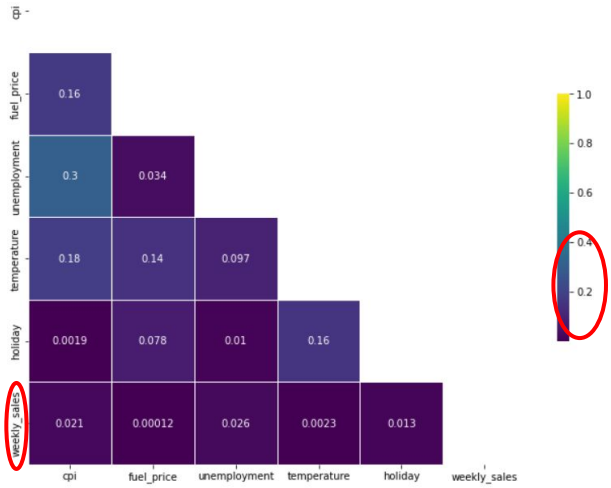
Future Research

- Deep multilayer perceptron
- Determine whether other features can be leveraged
- Develop active data pipeline to feed new data into the algorithm
- Deployment of real time forecasting updates to drive value for consumers and shareholders



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References

Aamer, A., Eka Yani, L. P., & Alan Priyatna, I. M. (2020). Data Analytics in the Supply Chain Management: Review of Machine Learning Applications in Demand Forecasting. Operations and Supply Chain Management: An International Journal, 14(1), 1–13. https://doi.org/10.31387/oscm0440281

Lin, H., Lin, J., & Wang, F. (2022). An innovative machine learning model for supply chain management. Journal of Innovation & Knowledge, 7(4), 100276. https://doi.org/10.1016/j.jik.2022.100276

Pan, Y. (2016, October 30). Notes for CS231n Recurrent Neural Network. www.yuthon.com/post/tutorials/notes-for-cs231n-rnn/

Skarica, V. (2022, January 3). 4 Demand Forecast Accuracy KPIs You'll Actually Use. Farseer. https://www.farseer.io/post/4-demand-forecast-accuracy-kpis-you-ll-actually-use#:~:text=Forecast%20error%20 numbers%20 range%20 from

Terlep, E. F., Costas Paris and Sharon. (2022, December 27). Supply Chains Upended by Covid Are Back to Normal. Wall Street Journal. https://www.wsj.com/articles/supply-chains-upended-by-covid-are-back-to-normal-11671746729

Tirkolaee, E. B., Sadeghi, S., Mooseloo, F. M., Vandchali, H. R., & Aeini, S. (2021, June 22). Application of Machine Learning in Supply Chain Management: A Comprehensive Overview of the Main Areas. Mathematical Problems in Engineering. https://www.hindawi.com/journals/mpe/2021/1476043/

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