An Auto Regressive Deep Learning Model for Sales Tax Receipt Forecasting from Multiple Short Time Series

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Background

- How to forecast sales tax receipts?
- "State lacks a good forecasting model" – Revenue Manager, Commission on Government Forecasting and Budgetary Accountability
- Usual suspects
  - Naïve models
  - Regression-based models
  - System models
- Issues
  - Volatility
  - Seasonality
  - Structural breaks/Instability

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(Relatively) New Approach: Deep Learning Methods

- Part of the "unsupervised machine learning" category of models
- Foundation are multi-layer perceptron models – a type of artificial neural network

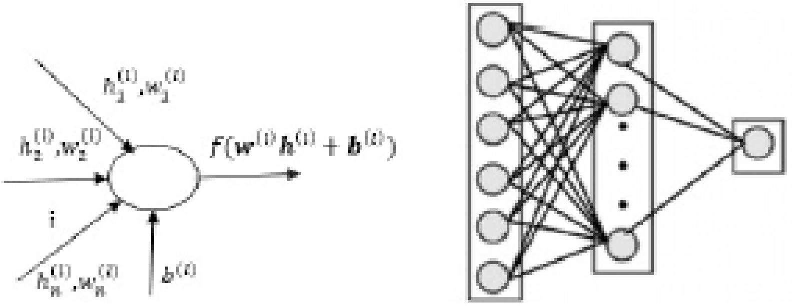

Fig. 1. Architecture of an MLP (on the right) and the functionality of a hidden neuron (on the left)

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Long-Short Term Memory Model

- A type of recurrent neural network, appropriate for time-series data
- Makes the weight at time *t* a function of inputs at time *t* and prediction at *t-1*
- Includes a **forget gate** and an **update gate**

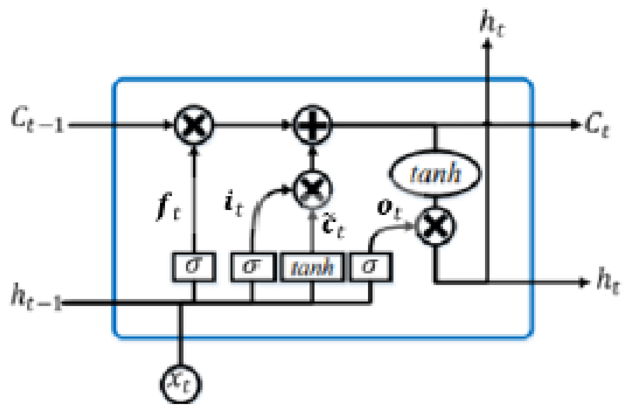

Fig. 2. An LSTM cell and its internal gating structure [15]

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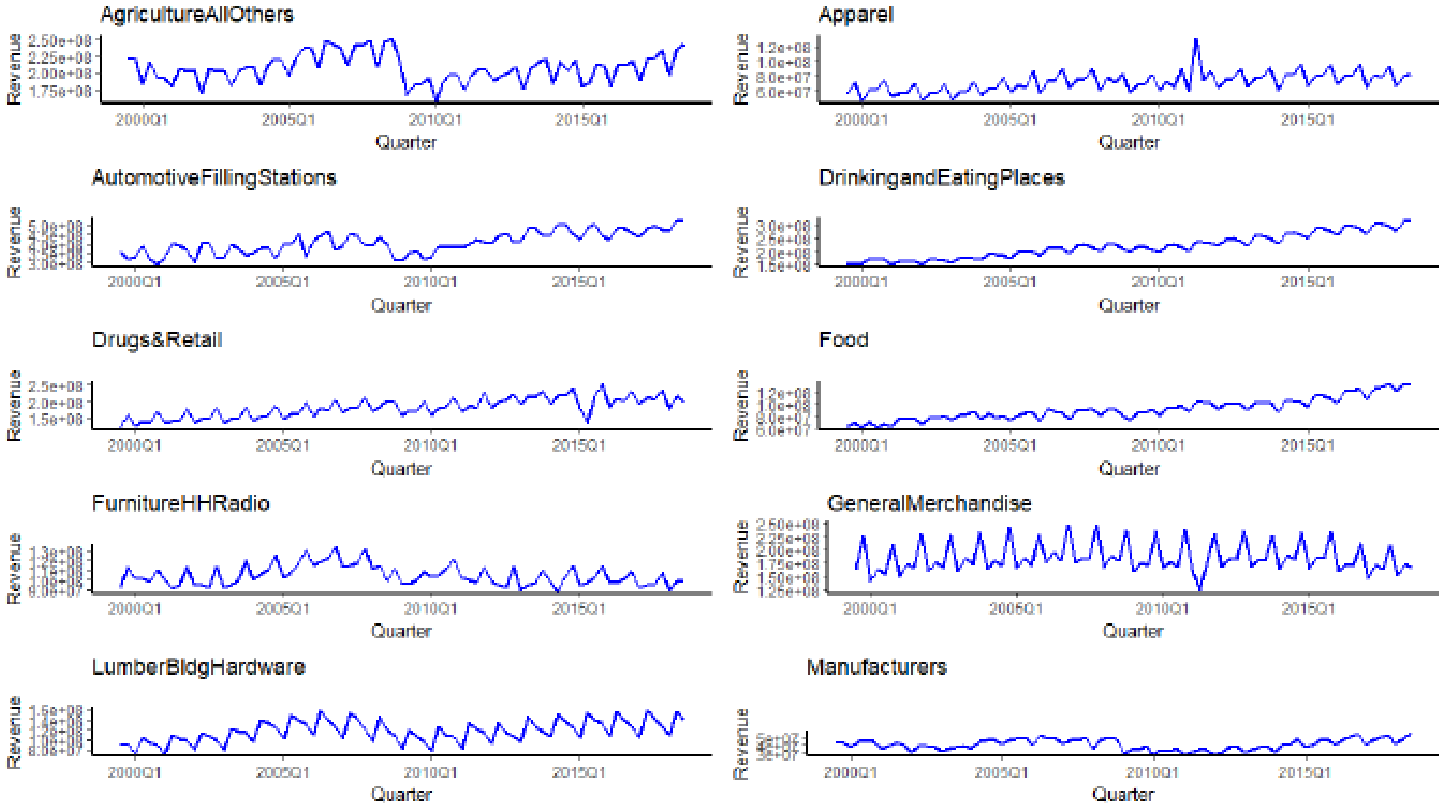
Data and Methodology

- Quarterly sales tax receipts by SIC industries, 1999-2018
  - T=77, n=10
  - Data is detrended and seasonally adjusted
- Compared forecast accuracy using MAPE
  - MLP
  - LSTM
  - ARIMA
- Walk-forward cross-validation

Time Series



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Results

TABLE I
COMPARISON OF THE ROLLING CROSS VALIDATION MAPE OF THE MLP AND LSTM MODELS VERSUS THE ARIMA MODEL FOR FORECASTING ILLINOIS SALE TAX RECEIPTS

	Agriculture AllOthers	Apparel	Automotive & Filling Stations	Drinking & Eating Places	Drugs & Retail	Food	Furniture & HHRadio	General Merchandise	Lumber Bldg & Hardware	Manufacturers	Mean across all categories
MLP	3.07	2.79	2.54	0.5	11.48	3.36	2.72	2.89	3.07	3.77	3.63
LSTM	4.16	4.16	4.44	1.47	10.69	3.91	3.04	5.34	4.0	6.80	4.80
ARIMA	5.51	7.39	3.34	3.87	9.87	8.03	5.06	9.50	6.85	3.91	6.33

TABLE II
THE VARIATIONS OF MAPE FOR THE GLOBAL MLP AND LSTM MODELS ACROSS 50 RUNS

		Agriculture AllOthers	Apparel	Automotive & Filling Stations	Drinking & Eating Places	Drugs & Retail	Food	Furniture & HHRadio	General Merchandise	Lumber Bldg & Hardware	Manufacturers
MLP	std	0.000427	0.000290	0.000274	0.000102	0.000895	0.000269	0.000272	0.000335	0.000268	0.000488
	min	2.95	2.71	2.49	0.57	11.31	3.29	2.67	2.80	3.02	3.67
	25%	3.04	2.77	2.53	0.58	11.43	3.34	2.70	2.86	3.05	3.73
	75%	3.10	2.81	2.56	0.59	11.53	3.38	2.74	2.90	3.08	3.80
	max	3.20	2.84	2.60	0.61	11.70	3.41	2.78	2.98	3.13	3.9
LSTM	std	0.005868	0.007879	0.009602	0.002171	0.011593	0.005424	0.004981	0.008250	0.004191	0.004191
	min	3.09	2.97	3.09	1.02	8.83	2.88	2.11	3.41	3.05	5.55
	25%	3.75	3.49	3.69	1.32	9.80	3.60	2.67	4.90	3.79	6.31
	75%	4.64	4.72	4.88	1.56	11.25	4.32	3.36	5.89	4.29	7.23
	max	5.17	5.69	6.89	2.13	13.31	5.16	4.06	6.60	4.72	8.21

Next Steps

- 4-period ahead forecasts
- Include regional effects
- Use other types of recurrent neural networks

SUPPLEMENTAL SLIDES

Specific Models

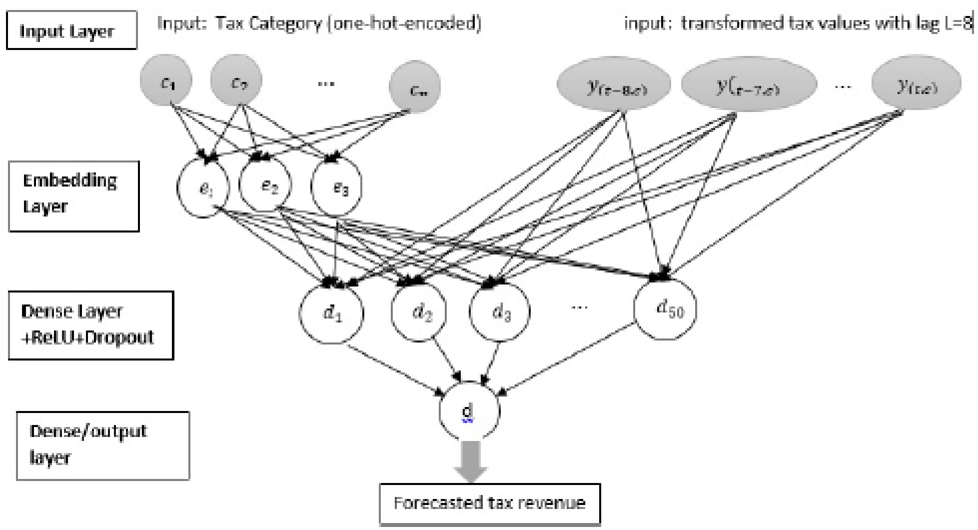

Fig. 5. MLP architecture for tax receipt forecasting