Sales Volume Forecasting Using Recurrent Neural Networks

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Overview of Red Ventures.

**HISTORY**

- Founded as Red F in 2000
- Red Ventures launched in 2004
- General Atlantic & SilverLake minority strategic investors.

**BY THE NUMBERS**

- 3,500+ Employees
- Locations
  - USA - 13 Locations
  - Brazil - Sao Paulo
  - United Kingdom - London
- 1 Culture
RV’s Business Model

The digital companion that help consumers to make purchasing decisions on **home**, **financial** and **healthcare** services

**Consumer Platforms**

- Reviews.com
- SaveOnEnergy
- GoodCall
- MYMOVE
- Choose Energy
- The Simple Dollar
- allconnect
- Bankrate.com
- CreditCards.com

**Partners**

- Home
- Health
- Fintech
RV’s Holistic Digital Marketing Platform

370MM unique visits and 6.1MM calls per year; 50TB of data; 1300+ cloud servers
Sales Call Volume Forecasting at RV

- Front-end Marking Effort
- Sales Call Forecasting
- Staffing/Scheduling
- Hiring
- Financial Planning

Time Horizon:
- Seconds
- Minutes
- Hours
- Days
- Weeks
- Months
Sales Call Volume Forecasting at RV

Other external factors
- Seasonality
- Holidays
- Social events
- Business specific events (e.g. offer changes)

Time Horizon
- Seconds
- Minutes
- Hours
- Days
- Weeks
- Months
How it was done in the past at RV

- Simple linear models + business logics
- Built and maintained by each business team with dedicated resources
- Labor intensive, not utilizing all the information available
- 10+% prediction errors in daily sales volume forecasting, not ideal for staffing and scheduling
How it is done at RV today

- Automated – can adjust itself to changes in the business and market
- Standardized – can be easily repurposed from one business to another
- Flexible – can take various inputs in addition to the time series history
- Adequate – more accurate and predictable performance for intra-day staffing and scheduling
Why Recurrent Neural Networks

Multi-object Tracking

Source: Anton Milan, AAAI, 2017
Why Recurrent Neural Networks

Multi-object Tracking

Automatic Text Generation

PANDARUS:
Alas, I think he shall be come approached and the day
When little strain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking as strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.

Second Lord:
They would be ruled after this chamber, and
my fair nues begun out of the fact, to be conveyed,
Whose noble souls I'll have the heart of the wars.

Clown:
Come, sir, I will make did behold your worship.

VIOLA:
I'll drink it.

Source: Andrej Karpathy, Stanford Univ.
Why Recurrent Neural Networks

Multi-object Tracking

Financial Forecasting

Automatic Text Generation

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Source: Anton Milan, AAAI, 2017

Source: Ravichandiran, YouTube

Source: Andrej Karpathy, Stanford Univ.
Background – Artificial Neural Networks

**Standard ANN**

- **Input**
- **Hidden Layer**
- **Weights**
- **Output**
Background – Artificial Neural Networks

Standard ANN

Input

Hidden Layer

Weights

Output

Summation

Activation
Background – Artificial Neural Networks

Standard ANN

Output
Hidden Layer
Weights
Input

Activation Functions

0/1 step
-1/1 step
relu: max(0, x)

sigmoid: \( \frac{1}{1+e^{-x}} \)
tanh: \( \frac{e^x - e^{-x}}{e^x + e^{-x}} \)

ReLU
Background – Recurrent Neural Networks
Background – Recurrent Neural Networks

Standard ANN

Output

Y

Hidden
Layer

H

Weights

W

Input

X

RNN

Output

Y

Hidden
Layer

H

Weights

W

Input

X
Background – Recurrent Neural Networks

Standard ANN

- Input: X
- Hidden Layer: H
- Weights: W
- Output: Y

RNN

- Input: X(t)
- Hidden Layer: H
- Weights: W
- Output: Y(t)

RNN unfolded

- Input: X(t)
- Hidden Layer: H
- Weights: W
- Output: Y(t)

...
Time Series Forecasting using RNN

\[
X(t) \rightarrow W \rightarrow H \rightarrow \cdots
\]

\[
X(t+1) \rightarrow W \rightarrow H \rightarrow \cdots
\]

Historical Data

Prediction Target

\[
X(t+1) \quad X(t+2) \quad \cdots \quad X(t+t_{\text{ahead}})
\]
Time Series Forecasting using RNN - Issues

Diminishing or Exploding Gradient

Model built through backpropagation
Time Series Forecasting using RNN - LSTM

LSTM

X(t\_t\_back)

\[ \cdots \]

X(t)

\[ \cdots \]

LSTM

X(t+1)

\[ \cdots \]

LSTM

X(t+1)

\[ \cdots \]

LSTM

X(t+1)

\[ \cdots \]

LSTM

X(t+1)

\[ \cdots \]

LSTM

X(t+1)

\[ \cdots \]

Prediction Target

X(t+1)

\[ \cdots \]

X(t+2)

\[ \cdots \]

X(t+t\_ahead)

\[ \cdots \]

Historical Data

The repeating module in an LSTM contains four interacting layers.

LSTM: Understanding Long Short-Term Memory Networks by Colah
Results

<table>
<thead>
<tr>
<th>Methods</th>
<th>Forecasting Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>RNN-LSTM</td>
<td>6.4% ± 5.2%</td>
</tr>
<tr>
<td>Baseline</td>
<td>11.2% ± 5.3%</td>
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</tbody>
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RNN vs Baseline: 3 Weeks
Results
Results

• Being rolled out to 7 different businesses with RV
• Free up business analyst resources
• Improve sales resource utilization
• Reduce call abandon rate