Roadmap

1. Introduction to Service Supply Chains & Thesis Focus
2. Data Set Generation
3. Methodology – Time-Series Forecasting
4. Methodology – Predictive Forecasting
5. Results and Data Analysis
6. Conclusions and Implications
1. Service Supply Chain Introduction

- Traditional supply chains deal with flows driven by customer demand

- Service supply chains deal with flows driven by product failure/customer dissatisfaction, and occur after the sale

1. Service Supply Chain Financial Impact

Consumer electronics industry

On average, warranty service costs represent 6% of total revenue

Apple

2.7% of Apple’s revenue

$4.6b (2013)

$4.9b (2014)
Within the last 5-10 years, the number of internet connected devices (commonly known as the “Internet of Things”) has exploded.

How can companies incorporate this information into their spare parts planning process?
Introduction to Service Supply Chains & IoT

Data Set Generation

Methodology – Time-Series Forecasting

Methodology – Predictive Analytics Forecasting

Results and Data Analysis

Conclusions and Implications
1. Data Set Generation

- Before comparing forecasting methods, needed to generate a demand data set to use in each of the two different methods

  - Accomplished by incorporating three different pieces of information:

```
Sales → Warranties → Failures
```
2. Data Set Generation

Sales are generated using the Bass Diffusion Model.

\[ A_t = m \times \frac{1 - e^{-(p+q)t}}{1 + \left(\frac{q}{p} \times e^{-(p+q)t}\right)} \quad t = 1, \ldots, n \]
2. Data Set Generation

- Warranty periods are assigned randomly to each machine sold
- Sales and warranty information create an installed base

<table>
<thead>
<tr>
<th>Warranty ID</th>
<th>Warranty Length (days)</th>
<th>Warranty Proportion of Population</th>
<th>Warranty Cumulative Proportion</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>156</td>
<td>0.3</td>
<td>0.3</td>
</tr>
<tr>
<td>B</td>
<td>260</td>
<td>0.7</td>
<td>1.0</td>
</tr>
</tbody>
</table>

- Warranty periods are assigned randomly to each machine sold
- Sales and warranty information create an installed base
2. Data Set Generation

![Diagram showing data set generation process]

\[ \lambda(t) \text{ over Maximum Warranty Lifetime} \]

\[ \lambda_t = \frac{\beta}{\eta} \times \left( \frac{a_{jt} - \gamma}{\eta} \right)^{\beta - 1} \]
2. Demand Set Generation

- Installed base and failure rate function create a simulated demand statement that we can use to test the two different forecasting models.

![Number of Failures vs Time Period Chart](chart.png)
Introduction to Service Supply Chains & IoT

Data Set Generation

Methodology – Time-Series Forecasting

Methodology – Predictive Analytics Forecasting

Results and Data Analysis

Conclusions and Implications
3. Time-Series Forecasting Methodology

- A time-series forecasting method forecasts future spare part demand based on the historical demand statement to date.
- We evaluate two different methods of time-series forecasting:

**Simple exponential smoothing**

\[ F_{t,t+1} = \alpha \cdot d_t + (1 - \alpha) \cdot F_{t-1,t} \]

**Simple exponential smoothing with trend**

\[ F_{t,t+1} = S_{t,t+1} + T_{t,t+1} \]

\[ S_{t,t+1} = \alpha \cdot d_t + (1 - \alpha) \cdot (S_{t-1,t} + T_{t-1,t}) \]

\[ T_{t,t+1} = \beta \cdot (F_{t,t+1} - F_{t-1,t}) + (1 - \beta) \cdot (T_{t-1,t}) \]
3. Time-Series Forecasting Methodology

- Forecast from time-series is plugged into R, S system
- To maintain certain level of service, we define a reorder point $S$. If the inventory level is under some level $S$, place an order of size $S$ less the current inventory position

$$S_t = \mu_{L+R_t} + z \cdot RMSE_{L+R_t}$$

$$Qp_t = \max (S_t - IP_t, 0)$$

RMSE is derived from error between forecast and actual demand over the last ten periods.
4. Predictive Analytics Methodology

- Predictive forecasting approach runs on a binary classification matrix.

- Assumes some analysis of a set of machine data has taken place and been compared to a related set of spare parts dispatches.

<table>
<thead>
<tr>
<th>actual value</th>
<th>predicted value</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>true</td>
<td>false</td>
<td></td>
</tr>
<tr>
<td></td>
<td>True Positive</td>
<td>False Negative</td>
<td></td>
</tr>
<tr>
<td></td>
<td>False Positive</td>
<td>True Negative</td>
<td></td>
</tr>
</tbody>
</table>

\[ TPR = \frac{tp}{(tp+fn)} \]

\[ FPR = \frac{fp}{(fp+tn)} \]

\[ PPV = \frac{tp}{(tp+fp)} \]

\[ NPV = \frac{tn}{(fn+tn)} \]
4. Predictive Analytics Methodology

<table>
<thead>
<tr>
<th>actual value</th>
<th>true</th>
<th>false</th>
</tr>
</thead>
<tbody>
<tr>
<td>true</td>
<td>True Positive</td>
<td>False Negative</td>
</tr>
<tr>
<td>false</td>
<td>False Positive</td>
<td>True Negative</td>
</tr>
</tbody>
</table>

\[
\text{predicted value} \quad \begin{array}{c|c|c}
\text{true} & \text{false} \\
\hline
\text{True Positive} & \text{False Negative} \\
\hline
\text{False Positive} & \text{True Negative} \\
\end{array}
\]

\[
\text{TPR} = \frac{tp}{(tp+fn)} \quad \text{FPR} = \frac{fp}{(fp+tn)}
\]

\[
\text{PPV} = \frac{tp}{(tp+fp)} \quad \text{NPV} = \frac{tn}{(fn+tn)}
\]

- **TPR**: Of the total number of failures, how many were predicted?
- **FPR**: Of the total number of non-failures, how many were falsely predicted?
- **PPV**: Proportion of signals that accurately predict a failure
- **NPV**: Proportion of non-signals that accurately predict a non-failure
4. Predictive Analytics Methodology

- We use the binary classification matrix and the size of the installed base to generate a forecast

1. Assign signals to failures using the TPR & FPR

2. Adjust signals based on the PPV and NPV

3. Plug forecast into R, S policy

\[ S_t = F_{t-1, t+1} + F_{t, t+2} + z\sqrt{V_{t-1, t+1} + V_{t, t+2}} \]

\( S \) covers demand in these periods
19

Introduction to Service Supply Chains & IoT

Data Set Generation

Methodology – Time-Series Forecasting

Methodology – Predictive Analytics Forecasting

Results and Data Analysis

Conclusions and Implications
5. Results & Data Analysis

- Each of the time-series forecasting models run 15x each
  - Find that exponential smoothing with trend model provides lower inventory while sustaining acceptable service level
  - Provides a baseline for comparison against predictive analytics model

<table>
<thead>
<tr>
<th>Metric</th>
<th>Measurement</th>
<th>Simple Exponential Smoothing</th>
<th>Simple Exponential Smoothing with Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Inventory</td>
<td>Average</td>
<td>8.884</td>
<td>8.592</td>
</tr>
<tr>
<td>CSL</td>
<td>Average</td>
<td>96.50%</td>
<td>95.98%</td>
</tr>
</tbody>
</table>
5. Results & Data Analysis

• The predictive forecast model was run 15x at each combination of the TPR and FPR in 10% increments between 0 and 1

• Allows for sensitivity analysis of varying levels of predictor accuracy

• New signals and demand statements created for each iteration of simulation in VBA
5. Results & Data Analysis

![Graph showing Variation in TPR (FPR = 0)]

- Service Level
- TPR
- Percent Inventory Reduction
- CSL
- IFR

4% 7% 10% 13% 17% 21% 25% 30% 36% 43% 63%

0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1

Percent Reduction in Inventory

0% 10% 20% 30% 40% 50% 60% 70%

0% 95% 96% 97% 98% 99% 100%
5. Results & Data Analysis

Variation in FPR (TPR = 1)

- Service Level vs. FPR
- Percent Reduction in Inventory

Graph showing the variation in FPR (True Positive Rate = 1) with service level and percent reduction in inventory.
5. Results & Data Analysis

• Each of the predictive forecasting models run 15x at each unique combination of TPR and FPR, in 10% increments of each.
5. Results & Data Analysis

- As confusion matrix provides more accurate results, less amount of variance in our forecast.

- In turn, this drives down the necessary safety stock to reach a certain service level until reaching 0, leaving only the cycle stock and reaching the minimum possible average inventory.

\[ \text{TPR} & \text{FPR} \]
6. Conclusions and Implications

• Provides concrete method for meshing together predictive analytics with spare parts inventory planning

• Could:
  • Potentially represent a significant reduction in working capital for companies as they are increasingly able to squeeze inventory out of their supply chain
  • Reduce total penalty costs paid in SLA/warranty servicing as companies are able to get a better jump start on service request ahead of time
  • Potential redesign of service supply chain network to aggregate inventory across multiple local spare parts field depots & trunk stocks into more centralized locations
    • reduction in shrinkage, obsolescence and damage
Questions?