Long and Short Term Forecasts and Weekly to Interval Staffing Requirements

Ric Kosiba
What we are discussing today

- Why we forecast, what we’re looking for, and the standard forecasting process
- Common forecasting issues
- How to handle outliers and missing data
- Forecasting from long term to short term
- Model sensitivity
- Taking a forecast and turning it into headcount
Why do we forecast?

- Forecasting is just one part of the planning process
- We forecast to make resource decisions!

- What types of contacts to service?
- How do we best match channels to segments of customers?
- What standards are right for each contact type?
- Where (which centers and staff types) and when (which weeks) do we hire?
- Hiring versus overtime?
- How many centers are optimal?
- Budgets and budget priorities?

... and so much more
What should you forecast? Everything!

Predicting shrink is as important as volumes!
(and AHT, and attrition, and backlog...)

Our goal: Accurate and consistent forecasts!

We need to:

- Capture the seasonality and trends of our operation (on all metrics) and test for accuracy
- Maintain consistency: forecasts cannot change with one new data point (otherwise we would have a new budget every week)!

This is for long term decisions (staffing, budgeting, and big-picture what-ifs)
Our goal: Accurate and consistent forecasts!

We need to:

- Maintain an accurate (and evolving) intraweek distribution
- It must roll up appropriately across weeks
- Monthly views must be consistent (end days are a problem)

This is for short term decisions (planning training, expected overtime/undertime, team meetings, etc...)

Short term forecast (daily)
Our goal: Accurate and consistent forecasts!

We need to:

- Account for time zone differences and changes
- Understand how the hourly distribution is shifting
- Understand regular events that skew daily forecasts (e.g. 1\textsuperscript{st} and 15\textsuperscript{th}…)

This is for short term decisions (early leave today, overtime expected, cancelling meetings, bringing supervisors onto the floor, etc... )

Short term forecast (interval)
Our goal: Accurate and consistent forecasts!

We need to be able to roll up, roll down, and be accurate, whether forecasting volumes, handle times, uncontrollable shrink (forecasting), or whether accounting for work hours and controllable shrink (staffing)
There is a standard forecasting process

Source, organize, and “clean” data
- Get data
- Look for anomalies
- Smooth outliers

“Describe” data
- What is the seasonality?
- Is it growing, shrinking, or stationary?

Model and prove
- Choose appropriate statistical method(s)
- Choose model parameters
- Understand error on hold-out sample

Evaluate and add judgment (or scenarios)
- Does the forecast make sense?
- Are there possible scenarios that history isn’t aware of?
Some common forecasting issues
Not enough data (there’s different sorts)

- Simple lack of data: Variability seems relevant, when it isn’t (especially small intervals)
- Warm up data: Exclude data that is un-representative, (i.e. when starting a new contact type)
- Small numbers: When forecasting for small contact streams, variability is high! Requires even more data, if possible
- Granularity: Your forecast cannot be at a level below your data (e.g. you cannot forecast skills if you only have roll up data, or cannot forecast 5 minute intervals if you have 15 minute data)

Naman’s Rule: two parts history to one part forecast
What to do when you simply don’t have much data??

Requires (engineering) judgment!

◦ Look at other contact streams if available?

◦ Try to measure growth, but also guesstimate a seasonality??

◦ Tie to another metric, like marketing data?
Too much data (clean/purge your data!)

Data you do not want:

- Zeros: It can mean no contacts or mean missing data
- Outliers: Data that is out of the ordinary (known or unknown), or a significant change
- Old situation: Something has changed in our contact center network. Do we want to use this data to forecast? (Answer: it depends)
- Warm-up or unrepresentative data
Source and Clean Data

1. Data needs to be accessible

2. Must find anomalous data
   - Outliers—unexplained change
   - Data we know is wrong. Data hiccup? Missing data? Flagged?
   - Non-repeating, one-off events

3. Smooth or “correct” anomalous data
Outliers and Calendar Day Effect

**Outliers**
- Anomalies in data, can be transitory or permanent change
- Outliers impact model selection, parameter estimates & forecast
- Types of outliers:
  - *Additive Outliers (AO)* – Random pulse / spike in data
  - *Level Shift (LS)* – Global change in trend
  - *Temporal Change (TC)* – Random pulse with trailing / decaying effect (e.g. marketing event)

**Special Events / Calendar Day Effect**
- Holidays, special events, leap years can have significant impact on forecast
- Also includes leading and lagging effect on calendar day
Can we get a computer to do this? Yes!

Three odd data points. How can a computer find these?
Interesting method:

1. Build a rough forecast, using a standard method, and keep track of the forecast “error”
2. Assume the forecast is correct
3. The data point farthest away from the forecast (say 3 standard deviations from the mean) is considered an outlier and should be replaced by the forecast
4. Repeat until no more outliers
More iterations

When finished iterating, you have “cleaned” and removed outliers. Question—does a human need to check the machine??
Missing Data Imputation

Missing data is automatically imputed

Missing data imputation is crucial to ensure long-term pattern is properly captured!
Short Term Forecasting

- Simple WFM forecasters—uses last few weeks of data to forecast the next week
  - Issue! You cannot forecast volumes (well) if you do not see seasonality
  - Example: Can you forecast the week after Christmas using this method?

![Graph showing volume forecast with confidence bounds](image-url)
Short Term Forecasting

Better:
- Use a few weeks to forecast a forecast distribution (more is better), but keep the latest long term forecast as the driver of volume. Short term for distribution, long term for volume
- Exception: rest of the day forecast is based on current daily trend

Best:
- Forecast each day separately? All Mondays, all Tuesdays, …

Either method will ensure that the forecast is consistent from interval to daily to weekly to monthly.
(Naman’s Rule does not apply short term)
Forecasting intervals way too far out

You shouldn’t worry about noon on January 13th in July

Intervals are useful when building schedules and for planning the next 2 weeks

Plan to a week over week level when putting together capacity, operational, and budget plans
Forecast Sensitivity

- One new data point should not change your forecast (much)
- Should one data point change your budget?
- There are math approaches that
  1. are accurate
  2. are not wildly sensitive
Validating models (what humans can do)

Use this part of history to build statistical forecasting models. This data “trains” your model.

Is the model accurate? Well if it passes a statistical accuracy test on the “test” data, then it is our best guess as to whether the model will work in the future.

Use this part of history to test whether your model works on parts of the history that were not used to build the model. This is “test” or “hold out” data.
Cross-validating (what computers can do (better))

When evaluating different forecasting methodologies against a time series data, the question then becomes which of these methodologies is best used for forecasting activity. Cross-validation is the most robust process to use in order to select the best-of-the-best forecasting methodologies.
When evaluating different forecasting methodologies against a time series data, the question then becomes which of these methodologies is best used for forecasting activity. Cross-validation is the most robust process to use in order to select the best-of-the-best forecasting methodologies.

Cross-validation ensures that the method chosen remains a favorite as more data is added. It ensures the forecast model is robust (and not too sensitive).
Forecasting methods

Stationary
• Simple moving average
• Point estimate single exponential smoothing
• Point estimate weighted average
• Single exponential smoothing

Seasonal
• Holt Winters (many flavors)
• Additive decomposition
• Multiplicative decomposition
• ARIMA

Trends
• Simple moving average
• Point estimate (many flavors)
• Linear weighted moving average
• Double Moving Average
• Double exponential smoothing
• Damped linear exponential smoothing
Finding the best parameters for each model

- Each method has a set of parameters that describe the slope, periodicity, etc… The goal for the forecaster is to find the set of parameters that develop forecasts that reduce forecast error on the holdout data.

- Humans can guess and test... but computers (cloud) can test every combination of every parameter of every method, and fairly quickly!
Forecast with validation

Forecast of Calls Offered for WEEKLY data

- Training data and fitted model
- Test
- Forecast
Changing gears: validating simulation models

Preferred Service: Service Level Comparison Simulation vs. Erlang-C vs. Actuals (Weekly Summary)

Preferred Service: Staffing Requirement Comparison Simulation vs. Erlang-C vs. Actual Staff FTE (Weekly Summary)

<table>
<thead>
<tr>
<th>Call Type</th>
<th>Avg. Error Sim</th>
<th>Avg. Error Erlang-C</th>
<th>Avg. Abn Rate (%)</th>
<th>Avg. SL (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loans</td>
<td>0.01%</td>
<td>27.34%</td>
<td>7.93%</td>
<td>76.45%</td>
</tr>
<tr>
<td>Member Services</td>
<td>-1.02%</td>
<td>30.91%</td>
<td>5.53%</td>
<td>84.70%</td>
</tr>
<tr>
<td>Preferred Services</td>
<td>2.69%</td>
<td>21.14%</td>
<td>2.93%</td>
<td>73.55%</td>
</tr>
<tr>
<td>Retail</td>
<td>-0.09%</td>
<td>-0.93%</td>
<td>1.05%</td>
<td>98.61%</td>
</tr>
<tr>
<td>Credit Card</td>
<td>-4.31%</td>
<td>5.92%</td>
<td>7.23%</td>
<td>55.87%</td>
</tr>
<tr>
<td>Auto Insurance</td>
<td>-1.90%</td>
<td>0.31%</td>
<td>1.32%</td>
<td>87.19%</td>
</tr>
<tr>
<td>SUMMARY</td>
<td>-0.77%</td>
<td>14.12%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Descriptive Models
Requirements from low to high level

- Validation of simulation models does an important thing (in addition to proving accuracy): it ties directly work hours, AHT, and volume to service level, ASA and ABN
- This tells us that if we can know how many hours we will have, given a forecast, we can predict service exactly at a weekly or daily level
  - We are calibrating total staff to SL, including inefficiencies (sked efficiency, non-adherence, absenteeism, etc…)
  - This means our staffing numbers are very close to produced schedules
- The killer idea: headcount staffed corresponds to headcount scheduled and managed
- We do not need to know schedules, just headcount

Rollups of staffing and scheduling are very, very close!
Final Thoughts

- **Forecast Everything**: Volume forecasts are important, but also are shrinkage, handle times, attrition,…

- **Automate**: So much of forecasting drudgery can be removed by taking time to code

- **Embrace the Future**: Cloud computing will bring opportunities to improve every stage of Customer Experiences— even forecasting and planning
What is Decisions?

- Decisions is a long-term contact center strategic planning and what-if analysis system.
- Because it is fast and accurate:
  - Perform risk and sensitivity analysis of your contact center
  - Evaluate center what-ifs: investments, consolidation, and growth opportunities
- Decisions complements traditional workforce management software by focusing on strategic decision making and long-term planning
Thank you, and (please) sign up for the next webinar!

Ric Kosiba, Vice President, Genesys Workforce Systems
ric.kosiba@genesys.com
410-224-9883