Goals for a predictive analytics model

• Pricing
• Revenue projection
• Visitation and attendance behavior
• Products and offers
The Barnes Foundation / WCAI

Summary of findings

May 16, 2019
Executive summary

• Barnes asked WCAI to help anticipate attendance
• WCAI modeled non-member and member attendance, testing three drivers:
  ▪ Barnes effects (e.g., pricing and exhibits)
  ▪ Competitive effects (e.g., peer pricing and attendance)
  ▪ Macro effects (e.g., seasonality and unemployment)
• Models were selected on the basis of statistical robustness, stability, and business intuition
• Most important factors were pricing, special events / exhibitions, and seasonality
• Models anticipate moderate declines in attendance in a “do nothing” scenario; however price discounts and special exhibitions/events arrest decline
The Barnes Foundation has a storied 96-year history – but has only been in Philadelphia since 2012

A brief history of the Barnes Foundation

- Alfred Barnes buys land in Merion, PA
- The Barnes Foundation opens
- Laura Barnes opens the Arboretum
- Public allowed regular access to collection
- Barnes proposes move to Philadelphia
- PHL groundbreaking; membership jumps from 400 to 20,000
- Barnes reopens in Philadelphia

Source: The Barnes Foundation; The New York Times (A Museum, Reborn, Remains True to its Old Self, Only Better)
The relocation has made it difficult to anticipate attendance – only recently is there sufficient history to model demand.

Barnes attendance since relocation

Source: The Barnes Foundation
WCAI sought to deliver a demand forecasting model to effectively use the data Barnes has collected.

### Our task

<table>
<thead>
<tr>
<th>Project goals</th>
<th>Design choices</th>
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<tbody>
<tr>
<td>• Provide “do-nothing” attendance forecast</td>
<td>• Minimize analytical complexity</td>
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### Our deliverable

- Embedded in current reporting templates
- Requires no additional work to use and update

![Forecasting Model Example](image-url)
### We approached the problem in three steps

<table>
<thead>
<tr>
<th>Step</th>
<th>Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td><strong>Define model structure</strong>&lt;br&gt;• How should we segment the population?&lt;br&gt;• Over what time step should we model?&lt;br&gt;• Segment for populations that have different expected demand drivers and historical experience&lt;br&gt;• Select granular time step while minimizing “noise”</td>
</tr>
<tr>
<td>2</td>
<td><strong>Hypothesize demand drivers</strong>&lt;br&gt;• Which factors drive demand for each segment?&lt;br&gt;• Which factors are actionable by Barnes?&lt;br&gt;• Identify long-list of variables capturing Barnes actions, competitor actions, and macro factors</td>
</tr>
<tr>
<td>3</td>
<td><strong>Select model</strong>&lt;br&gt;• Given hypothesized drivers, which model best captures attendance?&lt;br&gt;• Filter for statistical significance &amp; business intuition&lt;br&gt;• Select top models by back-test performance&lt;br&gt;• Further filter on secondary statistical tests</td>
</tr>
</tbody>
</table>
Step 1: Define model structure (1/2)
We developed separate models for members and non-members

Basis for segmentation

• Members / non-members should respond differently to Barnes actions (e.g., prices)
• Historically observe different behavior
• More granular segmentation risks compounding model error for limited benefit

Source: The Barnes Foundation
Step 1: Define model structure (2/2)
We elected to model attendance on a quarterly time-step

Basis for decision

- Quarterly data smooths random variation in attendance, allowing us to **better** observe economic effects
- Quarterly forecasts are fit for budgeting and planning purposes

Source: The Barnes Foundation
Step 2: Hypothesize demand drivers
We expect demand to respond to Barnes actions, competitor actions, and macro factors

- Barnes actions
  - Prices / discounts
  - Special exhibitions

- Peer actions
  - Peer attendance over time measures
  - Historical trends

- Macro factors
  - Seasonality
  - PHL economic health (e.g., unemployment)
  - PHL cultural attraction health (i.e., attendance across institutions)

Non-members
- Member-only events
- New members added
- Membership drives
Step 2A: Hypothesize demand drivers (1/2)
We see a meaningful effect of special exhibits/events on attendance

Non-member attendance

- Shonibare Exhibit
- Glackens Exhibit
- Order of Things Exhibit
- Picasso Exhibit

Peaks in the non-member attendance often correspond with special exhibitions

Member attendance

- Exhibition Member Previews
- Student nights / First Sundays

Peaks in the member attendance often correspond with special member-only events
Step 2A: Hypothesize demand drivers (2/2)
We observe an inverse relationship between price and attendance

Non-member attendance and average price after discounts
QoQ % change

Correlation = -45%
Step 2B: Hypothesize demand drivers

Aside from sharing seasonal peaks and troughs, we don’t see a relationship between Barnes and the Philadelphia Museum of Art.

The trend in Barnes attendance appears to be independent of the Philadelphia Museum of Art, which has remained stable over time.

To the extent Barnes attendance is correlated to that of the Philadelphia Museum of Art, it primarily reflects seasonal peaks and troughs.

Comments

- The trend in Barnes attendance appears to be independent of the Philadelphia Museum of Art, which has remained stable over time.
- To the extent Barnes attendance is correlated to that of the Philadelphia Museum of Art, it primarily reflects seasonal peaks and troughs.
Step 2C: Hypothesize demand drivers
We see a strong seasonal effect for non-members, and a modest effect for members

Non-member attendance

Member attendance
Step 3: Select model
We filtered potential models to identify a short list of candidates

Filtering process

- **Statistical significance and economic intuition**
  - Reject all models that have variables with p-value > 5% or unintuitive signs

- **Back-testing performance**
  - Rank-order models on back-tested RMSE and $R^2$

- **Actionability**
  - Ensure models have Barnes-specific drivers, like pricing and special events

- **Stability**
  - Ensure models are stable to removing data, have acceptable confidence bands

Selected model
Step 3: Select model

Top models capture much of the variation in changes in visitation

Non-member attendance
QoQ percent change, actual vs predicted

Member attendance
QoQ percent change, actual vs predicted

<table>
<thead>
<tr>
<th>Variable</th>
<th>Predicted (out-of-sample)</th>
<th>Predicted (full sample)</th>
<th>Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>(29%)</td>
<td>3%</td>
<td>(22%) - (36%)</td>
</tr>
<tr>
<td>QoQ %Δ in price</td>
<td>(153%)</td>
<td>28%</td>
<td>(96%) - (209%)</td>
</tr>
<tr>
<td>New exhibit starting</td>
<td>10%</td>
<td>5%</td>
<td>1% - 20%</td>
</tr>
<tr>
<td>Quarter 2</td>
<td>52%</td>
<td>6%</td>
<td>40% - 64%</td>
</tr>
<tr>
<td>Quarter 4</td>
<td>29%</td>
<td>6%</td>
<td>18% - 41%</td>
</tr>
</tbody>
</table>

Note: Out-of-sample testing removes the last year of data and recalibrates model
Implication 1: Expect non-member attendance to decline ~10% year-on-year in a “do-nothing” scenario

Scenario

- No price changes / changes in discounts (i.e., average price remains constant at initial Q4 levels)
- 2 special exhibitions per year (in Q1 and Q3)

Predicted attendance as % of Q4 visitation

<table>
<thead>
<tr>
<th></th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted</td>
<td>83%</td>
<td>105%</td>
<td>87%</td>
<td>88%</td>
</tr>
</tbody>
</table>

Comments

- Anticipate ~10% decline in attendance year-over-year in a “do-nothing” scenario
- Finding stable to overweighting recent experience (e.g., only calibrating on data from 2015 Q3 yields same 12% reduction)

Caveats

- Model reflects experience over calibration period – i.e., it won’t capture stabilization effects that have yet to materialize
- In the long-run, expect attendance to stabilize – should update model regularly
Implication 2: Modest reductions in price can stabilize non-member attendance while remaining revenue-neutral

Scenario

- Reduce average price after discounts by 8.5% (equivalent to reducing undiscounted price from $25 to $22.90)
- 2 special exhibitions per year (in Q1 and Q3)

Predicted attendance as % of Q4 visitation

<table>
<thead>
<tr>
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<th>Predicted</th>
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<tbody>
<tr>
<td>Q4 (current year)</td>
<td>100%</td>
</tr>
<tr>
<td>Q1</td>
<td>95%</td>
</tr>
<tr>
<td>Q2</td>
<td>120%</td>
</tr>
<tr>
<td>Q3</td>
<td>99%</td>
</tr>
<tr>
<td>Q4</td>
<td>100%</td>
</tr>
</tbody>
</table>

Comments

- Model anticipates a 1% reduction in price contributes to a 1.5% increase in attendance – i.e., price reductions don’t reduce revenue
- Estimate on the high end of a survey conducted by the Morey Group on behalf of Barnes, finding a 1% reduction in price could generate 0.5% to 1.25% greater attendance
- Caveats
  - Demand will be less elastic as price falls
  - Should be strategic about the segments in which we use price as a lever
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![Attendance forecast](image)
## Implementation of Model – Q4 2018

<table>
<thead>
<tr>
<th></th>
<th>Q3 Actual</th>
<th>Q4 Barnes Forecast</th>
<th>Q4 Model Predicted</th>
<th>Q4 Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Visitors</td>
<td>34,278</td>
<td>36,370</td>
<td>40,137</td>
<td>39,270</td>
</tr>
<tr>
<td>Visitation Revenue</td>
<td>$797,055</td>
<td>$866,485</td>
<td>$933,281</td>
<td>$903,242</td>
</tr>
<tr>
<td>Average Ticket Price</td>
<td>$23.25</td>
<td>$23.82</td>
<td>$23.25</td>
<td>$23.00</td>
</tr>
<tr>
<td>Member Visits</td>
<td>6,186</td>
<td>7,375</td>
<td>6,116</td>
<td>9,253</td>
</tr>
<tr>
<td>Other Free Visits</td>
<td>10,572</td>
<td>11,100</td>
<td>10,777</td>
<td>10,268</td>
</tr>
</tbody>
</table>
# Implementation of Model – Q1 2019

<table>
<thead>
<tr>
<th></th>
<th>Q1 Budget</th>
<th>Q1 Model Predicted With Q3 Data</th>
<th>Q1 Model Predicted with Q4 Data</th>
<th>Q1 Actual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Visitors</td>
<td>29,260</td>
<td>31,587</td>
<td>39,160</td>
<td>31,203</td>
</tr>
<tr>
<td>Visitation Revenue</td>
<td>$608,575</td>
<td>$734,477</td>
<td>$801,994</td>
<td>$652,935</td>
</tr>
<tr>
<td>Average Ticket Price</td>
<td>$20.80</td>
<td>$23.25</td>
<td>$20.48</td>
<td>$20.92</td>
</tr>
<tr>
<td>Member Visits</td>
<td>5,800</td>
<td>4,585</td>
<td>7,194</td>
<td>7,110</td>
</tr>
<tr>
<td>Other Free Visits</td>
<td>7,050</td>
<td>8,878</td>
<td>8,310</td>
<td>10,617</td>
</tr>
</tbody>
</table>
Implementation – Other Outcomes

• Lowered prices for weekday premium tours
  • Improved participation and increased revenue
• Continuing to evaluate pricing as a way to increase visitation
• Refocused emphasis on data capture
• Model is easy to use and update
• More data will improve outcomes over time