Next Best Action in Call Centers: Contextually augmented predictive models

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This talk is about predictive analytics in call centers

Call centers are a dominant channel of Customer Relationship Management (CRM) for companies

Call centers have specific service characteristics

• Very process focused people engaged in repetitive tasks
• Customer service, Troubleshooting, Problem solving, Back-office work
• They have very low tolerance for technology disruptions
• Focused on metrics like Average Handle Time (AHT), Customer Satisfaction (CSat), First Call Resolution (FCR)

Companies are very careful in running call centers as they touch customers. A recent trend for call centers has been to leverage them for revenue/profit

• Agents may be additionally tasked with selling activities
“Getting closer to the customer” is THE top priority for CEOs

Dimensions to focus on over the next 5 years

- Getting closer to customers: 88%
- People skills: 81%
- Insight and intelligence: 76%
- Enterprise model changes: 57%
- Risk management: 55%
- Industry model changes: 54%
- Revenue model changes: 51%

Source: Q13 Which of the following dimensions will you focus on more to realize your strategy in the new economic environment over the next 5 years? n=1,523, n=303

Source: IBM’s 2010 Global CEO Study – Capitalizing on Complexity (1,541 CEOs, 60 nations, 33 industries)
Customer intimacy is becoming increasingly challenging

The customer speaks with an agent over the phone, seeing minimal information.

The agent has minimal customer knowledge, sensing neither frustration nor up-sell opportunities. They can only offer a standard list of ‘hot products.’

56% report having to re-explain an issue
59% report expending moderate to high effort to resolve an issue
62% report having to try repeatedly to resolve an issue

The bad service ripple effect

Customers who are likely to say something positive about their customer service experience: 25%

Customers who are likely to speak negatively: 65%

Customers with a positive service interaction who told 10 or more people about it: 25%

Customers with a negative experience who told 10 or more others: 48%

Over 2.5x

Almost 2x
Call centers become effective when they move from cost levers to technology levers.
Levels of Analytics used in Call Centers

Most call centers today are at level 2 or 3 (some at 4)

1. No Analytics
   - Pure dependence on labour and processes

2. Reporting
   - Some KPI reporting and dashboards

3. Batch Analysis
   - Offline analysis of processes, structured/unstructured data mining including text analytics

4. Reactive
   - Decision support systems; e.g. banks routinely present customer propensity scores to call center agents for sales purposes

5. Proactive
   - Targeted customer dialog and real-time decision support in the hands of the call center agents
Predictive analytics in the hands of call center agents

- A nice deployment challenge for predictive analytics
- Tests scalability and integration capability in real-world situations
- We present Next Best Action for Call Centers (NBACC) in this talk
  - Dynamic predictive models in hands of call center agents
  - Real time decisions with directed information gathering
- We present a deployment case study for a global bank’s call center
- Results and future directions
Predictive models for customer buying propensities are standard. However the agent-customer conversation is an invaluable source of new contextual features for predictive models.
Case Study: Sales improvement for major global bank

Business Problem:

For their card activation queue, our client was struggling to maximize the cross-sell/up-sell revenue per activation call. The agents making the offers to new and existing customers had a predetermined “palette” of products to offer customers, but often defaulted to the easiest to sell which was not in line with the client’s sales strategy.

- Good Conversion Rate but not optimal revenue per closed sale
- No systematic way for Agents to optimally offering products to customers
- No way to factor in business rules based on the context of the conversation
- Sales Palette loosely based on profile and not customized

Approach:

NBACC was designed to provide the client with a cost effective program encompassing processes, analytics and technology with a goal to enhance the revenue per new card activation. Predictive analytics was made available to the agent during the phone call in real-time

- Leverage real-time information from conversation between agent and customer
- Deliver optimal product order for each customer as conversation proceeds
  - Reprioritize sales palette per customer
  - Deliver palette to agent in real time
- Minimize and mitigate impact of new processes on agents
A deployment scenario

Client premises

- Customer data warehouse in client’s own environment
- Live or periodic data sync

Call center premises

- Contact Center telephony and IT infrastructure
  - Call Center agents
- Real-time scoring requests
- Analytics Data mart
- Real-time analytics platform
- Back-end infrastructure

Customers on phone
- Analytics staff
Flow during agent-customer interaction

1. Customer call begins
2. Agent using NBA GUI
3. Agent initiates NBA
4. Display initial product offers
5. Retrieve profile and offers
6. Agent iteratively gathers information as Q&A
7. Decision & Question logic, and Business Rules
   Analytics staff
   Queries
8. NBA Analytics DB
9. Customer accepts or rejects offer
10. Final product recommendation to customer
11. Call ends
NBACC Architecture view

Client Propensity models

DB - Local Data Store (Online)
- Customer Propensity scores
- Customer Historical Insights
- Customer Current Insights

Dynamic propensity scoring

Real-time exec Platform
- Offers and Business Rules

Real Time Analytics

Action / Offer Recommendations

Dynamic propensity scores

Browser based agent interface for agent inputs and displaying the generated recommendations

Textual inputs by agent (analyzed offline to assess need for additional response codes or agent training)

Structured & unstructured inputs by agent

Business analyst configures offers and business rules

Trigger for generating recommendation

Custom developed components
- IBM software products

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A sample sales call in a travel portal’s call center

John, 30, Unmarried, Professional, Adventure sports enthusiast

Good morning, John. Great to hear from you again. How was your sky-diving trip last month?

Hi, it was great, thanks to your deals. I want to now ask about Beach packages for November.

John never goes to the Beach. Maybe scuba diving is apt for him? Let me ask.

John, may I ask you why a beach instead of this great skiing option I have for you in the Alps?

Well I am getting married next month. We have thought of a honeymoon near the beach.

That is excellent John. Congrats! I have this great Beach Spa package for you in romantic Bali for you then.
We want to outperform standard predictive customer propensity models based on historical data. The only hope is to have better contextually relevant features for prediction.

The agent-customer conversation is an invaluable source of information:

- Agents can actually understand the customer and context
- Agents can gather new predictive features if appropriately directed
- These features can augment or re-execute existing propensity models
Example for decision trees

- Predictions may lack confidence
- Models may be built on historical data with missing values in practice
- Inspection can help you turn nodes into “Spa vs. Scuba” questions
- Carefully crafted business rules can then strengthen recommendations
- There can be other such tweaks for other predictive models (SVMs)
The global bank’s call center

<table>
<thead>
<tr>
<th>Credit card queue</th>
<th>One of the several call center queues was credit cards</th>
</tr>
</thead>
</table>
| Agent activation and additional sales | Agents activated cards and sold additional products  
  - Additional cards  
  - Balance Transfer  
  - Insurance  
  - Credit Limit Increase |
| Customer context | Understanding the customer context and situation was expected to give better insights into what products were most appropriate |
| Time sensitivity | In a call center environment this had to be done while being sensitive to handle time and customer satisfaction while not stressing agents |
As per customer types, the questions to ask and the sequence in which to ask them was designed carefully.

### Questions and Rules for Selection and Sequencing

<table>
<thead>
<tr>
<th>Q. ID</th>
<th>Question Text</th>
<th>Response Choices</th>
<th>Qualifying Rules based on customer’s profile</th>
<th>Qualifying Rules based on product eligibility</th>
<th>Selection Rank</th>
<th>Sequencing Rank</th>
</tr>
</thead>
</table>
Run-time Propensity Deltas

Propensity scores are adjusted by an **additive delta factor** based on question responses

<table>
<thead>
<tr>
<th>Q. ID</th>
<th>Response Choices</th>
<th>Propensity Δs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>AC</td>
</tr>
<tr>
<td>$Q_1$: Hold other Card?</td>
<td>YES</td>
<td>-0.1</td>
</tr>
<tr>
<td></td>
<td>NO</td>
<td>0.2</td>
</tr>
<tr>
<td>$Q_2$: Liked which Feature</td>
<td>REWARDS</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>INTEREST RATE</td>
<td>0.2</td>
</tr>
<tr>
<td></td>
<td>BOTH EQUALLY</td>
<td>0.2</td>
</tr>
</tbody>
</table>
Agent screen

May I ask a few questions to help match our offers for you?

Yes please do

Would like a beach or a mountain vacation?

Option 1: Beach
Option 2: Mountain

Are you married?

Option 1: No
Option 2: Yes

Yes

Offer the spa in Bali
In a call center environment, performance metrics (AHT, CSAT) are critical and even linked to agent pay/bonuses.

Introducing NBA’s analytics driven methodology bound to adversely impact handle time in the short term (Needs careful training and intervention with agents).

Enterprise specific and cultural factors play a crucial role in interaction design.
# Measurement for reporting and analysis

## Test design and timing

<table>
<thead>
<tr>
<th>Agent Teams</th>
<th>Week 1</th>
<th>Week 2</th>
<th>Week 3</th>
<th>Week 4</th>
<th>Week 5</th>
<th>Week 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>Train</td>
<td></td>
<td>Measure</td>
<td>-- No NBACC --</td>
<td></td>
<td></td>
</tr>
<tr>
<td>T2</td>
<td>-- No NBACC --</td>
<td></td>
<td></td>
<td>Train</td>
<td>Measure</td>
<td></td>
</tr>
</tbody>
</table>

## Measurement metrics

- Offers made at various ranks
- Acceptance rate of offers at various ranks
- Revenue Per Offer (RPO)
  - A better metric than Revenue Per Call (RPC)
  - Depends on agent incentives
  - Agents finally sell based on soft factors

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**Case Study:**

Major Global Bank
Revenue improvements

Over a 6 week period, usage of NBA always benefitted agents

Our target was to improve sales by 12%-14%

Note: We expect Team 1 to be better in Week3 and worse in Week6

Case Study: Major Global Bank

<table>
<thead>
<tr>
<th>Week</th>
<th>Team 1</th>
<th>Team 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>w1</td>
<td>$42</td>
<td>$43</td>
</tr>
<tr>
<td>w2</td>
<td>$44</td>
<td>$46</td>
</tr>
<tr>
<td>w3</td>
<td>$54</td>
<td>$47</td>
</tr>
<tr>
<td>w4</td>
<td>$62</td>
<td>$52</td>
</tr>
<tr>
<td>w5</td>
<td>$58</td>
<td>$64</td>
</tr>
<tr>
<td>w6</td>
<td>$51</td>
<td>$60</td>
</tr>
</tbody>
</table>
A closer look - metrics for dynamic ranking

Rankings made sense over all metrics: Offers made, Acceptance rate, RPO

Case Study: Major Global Bank

<table>
<thead>
<tr>
<th>Offers made</th>
<th>Acceptance rate</th>
<th>Revenue per offer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rank 1</td>
<td>Rank 1</td>
<td>Rank 1</td>
</tr>
<tr>
<td>Rank 2</td>
<td>Rank 2</td>
<td>Rank 2</td>
</tr>
<tr>
<td>Rank 3</td>
<td>Rank 3</td>
<td>Rank 3</td>
</tr>
</tbody>
</table>

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Results and quantifiable benefits

**Major Global Bank**

- **Sales Revenue**: Improvement in actual sales revenue per month > 20%
- **Optimize Revenue per Close**: Improvement in revenue per sale of greater than 10%
- **Improve Product Conversion Rates**: Improvement in conversion rate of approx 20%
- **Net Benefit**: Net benefit of greater than 20%

**Significant improvement in monthly sales revenue**

- Improvement in agent close rate
- Improvement in revenue per close
- Improved customer experience
Other benefits

<table>
<thead>
<tr>
<th>Benefit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Handle time minimized</strong></td>
<td>Handle time impact minimized after initial rise</td>
</tr>
<tr>
<td><strong>Improved product mix</strong></td>
<td>Improved product mix in what agents managed to sell than before-- Earlier agents relied on what was easy to sell</td>
</tr>
<tr>
<td><strong>Quick learning</strong></td>
<td>Novice agents were quickly brought up to speed with experienced sellers due to use of a systematic data driven sales tool</td>
</tr>
<tr>
<td><strong>Better prioritization</strong></td>
<td>Better resonance now with Bank’s priorities and targets-- Opportunities possible for demand shaping and inventory sensitive analytics</td>
</tr>
</tbody>
</table>
What’s next?

- **NBA**: Based on Next Best Action in Call Centers, move to Outcomes Based Interaction services
- **Pricing**: Move away from vanilla CRM BPO pricing models like time and material
- **Outcomes**: Needs an understanding of outcomes based services
- **Analytics**: Needs the confidence to pull off results driven by analytics
Pricing is fundamental to commerce and its structure can profoundly influence perception of products.

Does the pricing model encourage:
- Quality
- High performance
- Lower costs
- Efficiency

Or does it encourage:
- Increased footprints
- Increased headcounts
- Time spent
Or what if these pros decided time and materials was better?

Barber: “Let’s keep cutting more hair”

Pizza deliverer: “That will be two hours. How would you like your pepperoni arranged?”

Lawn mower: “I thought I’d give you crosshatch stripes like a baseball field. Do you like it?”

Dentist: “I like to drill and drill... nice and slow”
Factors that need to be in place for success

To succeed with an outcome based model, certain capabilities must be in place.

<table>
<thead>
<tr>
<th>Capability</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Confidence</td>
<td>Confidence in delivery capability to assume the risks involved with an outcome based model and instill confidence in clients.</td>
</tr>
<tr>
<td>Repeatability</td>
<td>Having done it over and over ensures no unexpected hiccups and dependable delivery even in different environments</td>
</tr>
<tr>
<td>Methodology</td>
<td>Process optimization and standard methodologies are already in place and can be leveraged throughout the engagement</td>
</tr>
<tr>
<td>History and experience</td>
<td>Knowing what to do when is critical</td>
</tr>
<tr>
<td>Deep knowledge</td>
<td>Being masterful at both the known and unknown challenges is key to navigating potential roadblocks</td>
</tr>
<tr>
<td>Deep arsenal of tools and techniques</td>
<td>Outcomes based approaches require a deep bench of analytics and process design capabilities</td>
</tr>
</tbody>
</table>
Thank you

Joint work with Kevin English, Rohit Lotlikar, Pradeep Pachigolla at IBM

Questions, Comments, Bouquets, Brick-bats

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Backup slides
## How outcome based analytics services work

<table>
<thead>
<tr>
<th>Desired outcome</th>
<th>Commission based (‘bounty’) model</th>
<th>% of sales revenue generated</th>
<th>Fees varied based on conversion rates</th>
<th>Fees varied based on CSAT/NPS</th>
<th>Vendor paid as a percent of savings</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Revenue Improvement</strong></td>
<td>Pay Vendor a flat fee for each sale. Vendor incented to maximize the right kind of sales</td>
<td>Vendor takes % of incremental cross-sell/up-sell or new customer sales only; pay only for what we sell beyond your current teams</td>
<td>Fees varied based on sales conversion rate</td>
<td>Eg Transaction rates varied based on NPS rate</td>
<td></td>
</tr>
<tr>
<td><strong>Customer Retention</strong></td>
<td>Pay Vendor a flat fee for each saved customer. Vendor incented to save the right customers</td>
<td>Vendor takes % on future revenue from existing customers</td>
<td></td>
<td>Eg Transaction rates varied based on NPS rate</td>
<td></td>
</tr>
<tr>
<td><strong>Customer Satisfaction</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Operational Cost saving</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Vendor paid based on operational cost savings delivered</td>
</tr>
</tbody>
</table>
Data Flow during the agent-customer interaction

- Agent enters customer ID
- Applicable questions for each customer
- Prior propensity scores for each customer
- Demographics, card features, account, snapshot, call records
- Batch propensity scoring (weekly run)

1. Agent enters customer ID
2. Select and sequence questions
3. Agent asks the questions to the customer one by one
4. Agent enters customer’s responses
5. Update propensity scores and offer ranking after each response to a question
6. Agent makes offers based on updated offer rankings