New methods and advanced analytics at the Bank of England

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Advanced Analytics Division

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*Disclaimer: Our views do not necessarily reflect those of the Bank of England (BoE) or any of its committees.
Outline

1. The Bank of England and Advanced Analytics (I)
2. Machine learning in a central banking context (I)
3. Sending firm messages: Text mining PSM letters (II)
4. Enhancing central bank communications with behavioural insights (III)

Every session (I - III) is 20min + 10min Q&A.
Bank of England (BoE)

“Promoting the good of the people of the United Kingdom by maintaining monetary and financial stability.”

- **Banknotes** (e.g. new polymer notes)
- **Monetary policy** (e.g. interest rates, QE)
- **Financial Stability** (e.g. stress testing)
- **Gold storage** (“the vault”)  
- **Markets** (MP implementation)

- **Payment & Settlement** (e.g. CHAPS)
- **Prudential regulation** (e.g. banking supervision)
- **Research** (e.g. SWPs, conferences, Bank Underground)
- **Statistics**

Advanced Analytics (AA) connects to most of these tasks.
The “AA Team’s” interlocking tasks

- Analytics
- Research
- Outreach
- Technology

AA is kind of an “internal consultancy” mostly collaborating with other parts of the institution.
Machine learning in a central banking context*

Chiranjit Chakraborty & Andreas Joseph

Introduction to machine learning (ML) *

- “Econometrics from computer scientists”
- Models as universal approximators (non-parametric non-linearities)
- Focus on prediction (correlation, not causation)
- Few asymptotic results (research needed!) **
- General policy problem includes a prediction component ***

* “Economists are prone to fads, and the latest is machine learning”, The Economist, 26. Nov 2016
ML modelling protocol (simplified)

1. Fit model on training data.
2. Set hyper-parameters ($\lambda$) by testing model on new data (cross-validation)
3. Final model test via out-of-sample testing (no asymptotics)

Full dataset

<table>
<thead>
<tr>
<th>60%</th>
<th>20%</th>
<th>20%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training data</td>
<td>Validation data</td>
<td>Testing data</td>
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</table>

Model estimation

Model calibration

Model evaluation

Gold standard out-of-sample testing
General policy problem

\[
\frac{d\pi(X, Y, Z)}{dX} = \left( \frac{\partial \pi}{\partial X} \right)_{Y} + \frac{\partial \pi}{\partial Y} \left( \frac{\partial Y}{\partial X} \right)_{Z}
\]

\(\pi\): payoff/welfare, \(X\): policy variable, \(Y\): outcome, \(Z\): controls

Examples:

- \(X\): umbrella, \(Y\): weather, \(\pi\): wellbeing
- \(X\): bank capital buffers, \(Y\): growth, \(\pi\): welfare

Potential central banking applications of ML

1. **Non/semi-structural modelling** (e.g. forecasting)
2. **Operational process optimisation** (e.g. supervision, conduct)
3. **Pattern recognition in large datasets** (e.g. variable extraction)
4. **Policy analysis** (e.g. payoff evaluations, often microeconomic issues)
5. **Dynamic policy simulation** (e.g. dynamically learning agents; similar to DeepMind’s [Mastering the game of Go (2016)](https://www.masteringgo.org/))
SWP case studies

1. Banking supervision: prudential regulation, financial stability

2. Inflation forecasting: monetary policy

3. Investigating Fintech funding structures: financial stability
Case: Banking supervision

- Detect “alerts” which my trigger further action on Banks’ balance sheets

- Stylised setting of incomplete information and non-trivial alert rule

- Data source: regulatory returns (international banks)

**Target (Y):** firms with >= 3 outliers / quarter out of 6 measures

**Inputs (X):** 4 measures (CP exp. Removed)

Sources: BoE staff calculation
<table>
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<th>CP exp. 2</th>
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<td>6</td>
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Sources: BoE staff calculation
## Model Comparison

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<tr>
<th>method</th>
<th>CV</th>
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<th>acc\textsubscript{test}</th>
<th>precision</th>
<th>recall</th>
<th>F\textsubscript{1}</th>
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<tbody>
<tr>
<td>naïve Bayes</td>
<td>Gaussian kernel</td>
<td>80.3</td>
<td>79.8</td>
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<td>35.4</td>
<td>40.2</td>
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<td>89.7</td>
<td>80.0</td>
<td>61.3</td>
<td>69.4</td>
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<tr>
<td>decision tree</td>
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<td>89.4</td>
<td>75.6</td>
<td>66.2</td>
<td>70.6</td>
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<td>91.6</td>
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<td>69.9</td>
<td>76.2</td>
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<td>Logit</td>
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<td>81.8</td>
<td>58.5</td>
<td>18.6</td>
<td>28.2</td>
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</tbody>
</table>

Sources: BoE staff calculation
Conditional predictions & feature importance

Tree models allow to calculate feature importance: error reduction across tree branches due to each variable.

Sources: BoE staff calculation
Thanks – Q&A
Sending firm messages: Text mining PSM letters*

David Bholat, James Brookes, Chris Cai, Katy Grundy and Jakob Lund

*SWP 688: “Sending firm messages: text mining letters from PRA supervisors to banks and building societies they regulate” (2017), BU post “Open letters: Laying bare linguistic patterns in PRA messages using machine learning” (2018)
Primary research question and hypotheses

Are PSM letters written differently to firms with different risk profiles?
  • *If so, what linguistic features distinguish sub-genres of PSM letters?*

We expected PSM letters to vary depending on firm riskiness
  • consistent with the PRA’s principle of proportionality

We expected higher risk firms to receive letters that were:
  • more complex
  • more negative in sentiment
  • more directive
### ‘Intrinsic risk’ = Potential Impact = Firm Category

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category 1</td>
<td>Most significant deposit-takers capable of <strong>very significant disruption</strong></td>
</tr>
<tr>
<td>Category 2</td>
<td>Significant deposit-takers capable of <strong>some disruption</strong></td>
</tr>
<tr>
<td>Category 3</td>
<td>Deposit-takers capable of <strong>minor disruption</strong></td>
</tr>
<tr>
<td>Category 4</td>
<td>Deposit-takers capable of <strong>very little disruption</strong></td>
</tr>
<tr>
<td>Category 5</td>
<td>Deposit-takers capable of <strong>almost no disruption</strong></td>
</tr>
</tbody>
</table>

Increasing risk
‘Imminent risk’ = PIF stage = proximity to resolution

<table>
<thead>
<tr>
<th>Stage 1</th>
<th>Low risk to viability of firm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stage 2</td>
<td>Moderate risk to viability of firm</td>
</tr>
<tr>
<td>Stage 3</td>
<td>Risk to viability absent action by the firm</td>
</tr>
<tr>
<td>Stage 4</td>
<td>Imminent risk to viability of firm</td>
</tr>
<tr>
<td>Stage 5</td>
<td>Firms in resolution or being actively wound up</td>
</tr>
</tbody>
</table>

Increasing risk
Secondary research question and hypotheses

Has supervisory communication measurably changed post-crisis?
  • If so, how do PRA PSM letters differ from FSA ARROW letters?

Compared to the ARROW letters, we expected the PSM letters to be:
  • more complex
  • more directive
  • more forward-looking
Linguistic features

- **Complexity**
  - e.g. length of letter, subordinate clauses
- **Sentiment**
  - e.g. balance of positive versus negative words
- **Directiveness**
  - e.g. obligatory phrases such as *should, must, expect*
- **Formality**
  - e.g. whether the salutation is handwritten or typed
- **Forward-lookingness**
  - e.g. future-oriented verb tenses
Random Forests

1. Category 1 vs. Category 2-4
2. PIF 1-2 vs. PIF 3-4
3. PSM letter vs. ARROW letter

~ 25 linguistic features
Random Forests

ALL LETTERS

training data  test data
ALL LETTERS

1  training  test
2  training  test
3  training  test
4  training  test
   …
2000 training  test
CAT 1 PSM letters different from CAT 2-4 letters

- More complex
- Less directive
- Less formal
- No differences in sentiment
PIF 3-4 PSM letters different from PIF 1-2 letters

- More complex
- More ‘high-risk’ vocabulary
- Less directive
- Less formal
PSM letters different from ARROW letters linguistically

- More complex
- More directive
- More forward-looking
PSM letters different from ARROW letters in content

Normalized frequency (%) of PSM 2015 section headings

- Capital Adequacy: 13.9%
- Risk Management and Controls: 10.8%
- Liquidity: 9.9%
- Board Management and Governance: 9.6%
- Recovery and Resolution Planning: 9.3%
- Business Model and Strategy: 8.6%
- Treasury and Asset Liability Management: 5.6%
- Credit Risk and Lending: 4.6%
- Relationship with regulators: 3.4%
- IT and Operational Risk: 3.1%
- Risk Appetite: 1.9%
- Authorisations: 1.9%
- CEO and Executives: 1.5%
- Supervisory Strategy: 1.2%
- Management Information: 1.2%
- Internal Models: 1.2%
- Internal Audit: 1.2%
- People Risk: 0.9%
- Basis Risk: 0.9%
- Other non-generic headings: 9.3%

<table>
<thead>
<tr>
<th>Section heading</th>
<th>Others</th>
<th>Common to both ARROW &amp; PSM</th>
<th>Unique</th>
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</thead>
<tbody>
<tr>
<td>Capital Adequacy</td>
<td></td>
<td>13.9</td>
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<td>Risk Management and Controls</td>
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<td>Liquidity</td>
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<td>Credit Risk and Lending</td>
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<td>Management Information</td>
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<td>Other non-generic headings</td>
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Summary

• Are PSM letters written differently to firms with different risk profiles?
  Yes

• Has supervisory communication measurably changed post-crisis?
  Yes
Thanks – Q&A
Enhancing central bank communications with behavioural insights*

David Bholat,\(^{(1)}\) Nida Broughton,\(^{(2)}\) Alice Parker,\(^{(1)}\) Janna Ter Meer\(^{(2)}\) and Eryk Walczak\(^{(1)}\)

\(^{(1)}\)Bank of England - Advanced Analytics
\(^{(2)}\)Behavioural Insights Team

*forthcoming SWP
Central bank communications matter

• Good communication is powerful for central banks because it improves the effectiveness of our policies e.g. anchoring inflation expectations

• Good communication could potentially:
  - build awareness of what the Bank of England does and why
  - increase interaction and engagement with the content
  - enhance public trust and understanding
Research Objectives

• Measure the extent to which the **Visual Summary** improved public comprehension and trust in key messages from the Bank’s *Inflation Report* compared to the **Monetary Policy Summary**

• Our experiment also tested two new versions – one version with **Reduced Text** and one that restructures the information and uses **Relatable content**
The Bank of England’s Monetary Policy Committee (MPC) sets monetary policy to meet the 2% inflation target, and in a way that helps to sustain growth and employment. At its meeting ending on 7 February 2018, the MPC voted unanimously to maintain Bank Rate at 0.5%. The Committee voted unanimously to maintain the stock of sterling non-financial investment-grade corporate bond purchases, financed by the issuance of central bank reserves, at £10 billion. The Committee also voted unanimously to maintain the stock of UK government bond purchases, financed by the issuance of central bank reserves, at £435 billion.
The squeeze on pay is easing

Over the past year, prices have been rising faster than wages. That means people have not been able to afford as much. We think that is changing.

The share of people out of work is now at its lowest level since 1975. And there are a lot of job vacancies. This means that companies are having to compete hard with each other to recruit and retain workers. One way they do that is by offering higher wages — so we expect bigger pay rises over the next few years.

We think that pay will rise faster than prices this year, easing the squeeze on living standards.
A holiday abroad is more expensive now than it was before the Brexit vote.

A basket of goods and services that cost you £100 this year...

...should cost you £102 next year.

CHART: Look at what unemployment is like in your area

Select your region

West Midlands

Source: ONS data
## Treatments

Word count, readability and visual of different arms of the experiment

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Word count</th>
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<th>Number of Visuals (charts / icons)</th>
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<td>Visual Summary</td>
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<tr>
<td>Reduced Text Summary</td>
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<td>14</td>
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<tr>
<td>Relatable Summary</td>
<td>407</td>
<td>4.98</td>
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Contributions

- **Central bank communication literature and Vision 2020**
  - Identify new strategies for external communication
  - Expand literature on central bank communications
  - Expand the Bank’s methodological range

- **Behavioural economics literature**
  - From micro to macro decision-making
  - Central banks
Representative sample (2275 respondents) of UK population based on gender, age, income and regional location, assigned to one of the four groups.
Direct Comprehension questions

1. In what way does the Bank of England support the UK economy?
2. Based on what you have read, which of these is true about prices at the moment?
3. Based on what you have read, what has happened to the amount of people that are out of work recently?
4. Based on what you have read, what is likely to happen to how much people can afford to buy this year?
5. What is the Bank of England’s current interest rate?
Model specification

\[ Y_{i}^{\text{comp}} = \alpha + \beta_1 T1_i + \beta_2 T2_i + \beta_3 T3_i + \beta_4 \Gamma A_i + \varepsilon_i \]

• where \( Y_{i}^{\text{comp}} \) is treated as a continuous variable representing the number of correct answers to the comprehension questions for the participant \( i \)

• \( T1_i \) is a binary variable which indicates the treatment for participant \( i \) with a value of 1 if the participant is in the Visual Summary condition and 0 otherwise

• \( T2_i \) is a binary variable which indicates the treatment for participant \( i \) with a value of 1 if the participant is in the Reduced Text Summary condition and 0 otherwise

• \( T3_i \) is a binary variable which indicates the treatment for participant \( i \) with a value of 1 if the participant is in the Relatability Summary condition and 0 otherwise

• \( A_i \) is a vector of controls indicating the gender, age bracket, income bracket, region, and economics engagement level of participant \( i \)
  • \( \alpha \) is the regression constant
  • \( \Gamma \) is the coefficient of each control in \( A_i \)
  • \( \varepsilon_i \) is the error term
Results – Direct Comprehension

- **Monetary Policy Summary**: 2.02
- **Visual Summary**: 2.53
- **Reduced Text Summary**: 2.63
- **Relatable Summary**: 2.85

N=2,275
**p<0.01, *p<0.05, +p<0.1
“Your friend spends £100 a week on groceries. They are planning their household finances for next year, and are thinking about how much they need to budget for groceries. They want to keep buying the same things as they are now.

Based on what you have read, what do you think they should budget for their weekly grocery shop next year? What your friend spends each week on groceries now: £100”

“Your friend earns £100 per day. They will have a chance to ask for a pay rise at the end of this year to cover increases in the cost of living.

Based on what you have read, how much should they ask for, just to cover increases in the cost of living? Your friend’s daily rate (what your friend currently earns): £100 per day”
Results – Self-reported Comprehension (Haldane & McMahon measure)

“To what extent are you able to understand the content and messages of the material you just read?”

- Monetary Policy Summary: 2.82
- Visual Summary: 3.33
- Reduced Text Summary: 3.50
- Relatable Summary: 3.76

N=2,275
** p<0.01, * p<0.05, + p<0.1
Imagine someone is looking for trustworthy information about the economy. How would you rate the information on the website you have just seen? (0-10 point scale)
“Learning that this is typical communication in the Bank of England quarterly *Inflation Report*, how has the *Inflation Report* summary affected your perceptions of the Bank of England, if at all?” (1-5 scale)
Summary findings and implications

• The Visual Summary improves public comprehension relative to the Monetary Policy Summary

• The Visual Summary could be made more relatable to increase public comprehension and trust in the Bank’s policy messages.
Future research

• Relatability

• Trust

• Behavioural biases

• Media sources
Thanks – Q&A