The Role of Memory in Belief Formation

by Markus Mobius, Tanya Rosenblat and Pierre-Luc Vautrey

Abstract

A growing body of research has documented both systematic and motivated belief biases in decision making such as correlation neglect and wishful thinking. A better understanding of how people aggregate signals and form beliefs in the first place is crucial for understanding the origin of these biases and potential policy interventions. In this paper, we explore the role of memory in belief formation. We design a simple experiment where participants read a set of news sources which report naturalistic positive and negative facts about an artificial company. We provide enough information to participants about the fact-generating process so that they can form a Bayesian posterior on whether the company is "good" or "bad". We then (a) elicit participants' beliefs about the quality of company based on these narratives and (b) present participants with a superset of facts to determine whether they recognize previously seen facts. Just like real newspapers, facts can be repeated across several news sources. Unlike most of the existing literature on correlation neglect, our experiment introduces repetition through actually repeated signals which we argue is more natural than merely correlated signals. Our design therefore allows us to explore the role of recognition and recall in belief formation which are two fundamental concepts in cognitive psychology. We find that participants exhibit good recognition which is only slightly increasing by repetition of the signal. Participants slightly overweigh repeated signals (beyond what is accounted for by the greater recognition) but do not fully double-count. We propose two models of belief formation where agents either "replay" recalled signals or keep track of summary counts using the recognition channel and discuss how our experiment can distinguish between these models. Our framework can also help with understanding how individual (single-agent) learning differs from social learning.
The Role of Memory in Belief Formation

Markus Mobius
MSR and NBER

Tanya Rosenblat
University of Michigan

Pierre-Luc Vautrey
MIT

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“Your memory is a monster; you forget - it doesn’t. It simply files things away.”
– John Irving

Recent research suggests that agents make mistakes when aggregating repeated information.

- Double-counting in DeGroot social learning model
  - Chandrasekhar et al. (2018), Grimm and Mengel (2018)

- Correlation neglect and single-agent learning
  - Enke and Zimmermann (2017)
Motivation

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Evidence for correlation neglect is based on settings where agents learn from correlated posteriors.

- DeGroot learners listen to their neighbors’ opinions.
- Experiments with single-agent learning induce correlated signal structure.

However, in the real world, repeated information often presents itself simply as repeated signals.
Initially, sender has signal 20, and two intermediaries have signals 5. Receiver has no info.

Initial opinions are simply the signal.
Correlated Posteriors: DeGroot

Initially, sender has signal 20, and two intermediaries have signals 5. Receiver has no info.

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Sender communicates to intermediaries A and B who average the received signal with their own signal.
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Initial opinions are simply the signal.

Sender communicates to intermediaries A and B who average the received signal with their own signal.

Intermediaries communicate with receiver who averages both posteriors.

The sender neglects the correlation in the intermediaries’ posteriors and therefore overweighs the sender’s signal (under equal weighting her belief would be 10 instead of 12.5).
Subject has to learn average of A and B’s signals (think of them as news agencies).

Intermediary is just another computer that averages A and B (think of it as a newspaper).
Correlated Posteriors: Enke and Zimmermann (2017)

- Subject has to learn average of A and B’s signals (think of them as news agencies).
- Intermediary is just another computer that averages A and B (think of it as a newspaper).
- Subject learns A’s signal directly.

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Introduction

**Correlated Posteriors: Enke and Zimmermann (2017)**

- Subject has to learn average of A and B’s signals (think of them as news agencies).
- Intermediary is just another computer that averages A and B (think of it as a newspaper).
- Subject learns A’s signal directly.
- Intermediary communicates the average of A and B.

Subjects largely ignore the correlation structure and fail to back out B’s signal ⇒ hence they overweight news agency A.

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$s = 10$

Computer B → Intermediary 1

$s = 20$

Computer A → Subject

$t = 2$
Economic theorists appear to find it easier to unravel correlation structures than subjects in the lab.
Correlated Posteriors vs. Repeated Information

- Economic theorists appear to find it easier to unravel correlation structures than subjects in the lab.
- In many situations people consume *sets of facts* rather than posteriors.
  - News agency reports consist of a collection of facts rather than a summary opinion.
Correlated Posteriors vs. Repeated Information

- Economic theorists appear to find it easier to unravel correlation structures than subjects in the lab.

- In many situations people consume *sets of facts* rather than posteriors.
  - News agency reports consist of a collection of facts rather than a summary opinion.

- Aggregating facts can often be accomplished by only using *recognition* rather than *recall*.
  - *Recognition* is the ability to recognize a previously seen fact.
  - *Recall* is the ability to retrieve the details of facts from memory.
  - Ample research in psychology suggests that people can often recognize facts without being able to recall them.
Enke and Zimmermann (revisited)

News agency A has a story with one positive fact $P_1$ and one negative fact $N_1$. Agency B has positive fact $P_2$.

Intermediary is a newspaper that sources both agencies and reports $P_1$, $P_2$, $N_1$.

$t = 0$
Enke and Zimmermann (revisited)

- News agency A has a story with one positive fact $P_1$ and one negative fact $N_1$. Agency B has positive fact $P_2$.
- Intermediary is a newspaper that sources both agencies and reports $P_1, P_2, N_1$.
- Subject learns facts $P_1$ and $N_1$. She stores the summary statistic of net 0 positive signals.
Enke and Zimmermann (revisited)

- News agency A has a story with one positive fact $P_1$ and one negative fact $N_1$. Agency B has positive fact $P_2$.
- Intermediary is a newspaper that sources both agencies and reports $P_1$, $P_2$, $N_1$.
- Subject learns facts $P_1$ and $N_1$. She stores the summary statistic of net 0 positive signals.
- Intermediary communicates $P_1$, $P_2$, $N_1$. She recognizes facts $P_1$ and $N_1$ and ignores them. She only incorporates signal $P_2$ and her summary statistic is 1.
The distinction between recognition and recall when processing repeated information is captured by the concept of hash functions from CS.

- A hash function assigns a short checksum to a large object (fact).
  - It makes it easy to recognize the same object next time.
  - It takes less memory to store a hash instead of the full object.
- Hash functions do not allow recall/enumeration.
  - It is not possible to reconstruct facts from the hashes.
Hashed Social Learning

- As shown in the example before, individual hashed learning of repeated information with appropriate summary statistics can be efficient.

- However, social learning without recall is much harder.
  - A sender cannot transmit a list of previously heard facts to the sender without enumerating them.
  - Intuitively, the sender has to resort to sending summary statistics.
    - “I heard mostly good things about this company.”
    - This gives rise to DeGroot-like double-counting.
We use an experiment to study individual learning with repeated information.

- We use a naturalistic design where subjects see news articles that report facts about a fictitious company.
- Just like real news articles, the same facts can be reported more than once.
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Subjects’ beliefs are affected both by recognized and unrecognized facts.

Little double-counting with recognized facts.

Unrecognized facts affect beliefs more weakly and exhibit double-counting.
Welcome to our study.

Illustra is a (fictional) large US manufacturing company with offices around the world. On the following screens, you will be able to pick and read several news articles from various imaginary trade journals that will inform you about the business-relevant events that have impacted Illustra during the past three months.

You will earn $0.5 at the conclusion of the experiment as a thank-you for participating in this study.

After reading the news articles, we will ask you to assess Illustra’s business prospects and make a sequence of economic decisions. We expect most participants taking the study carefully to earn between $1 and $3. The study will take you no more than 15 minutes.

Read Consent Information
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Read Consent Information

Illustra is a fictitious company.
Instructions: Good/Mad Management

Please read the following carefully in order to make good decisions and maximize your earnings:

When you click on "Next", the computer will randomly choose the quality of Illustra’s management to be good or bad with equal probability. It will then simulate the life of Illustra for a few months by generating 8 events randomly, and independently of each other. If Illustra is well managed, each event that happens to Illustra will be good news with probability 70.0% and bad news with probability 30.0%; if it’s poorly managed, events that happen to Illustra will be good news with probability 30.0% and bad news with probability 70.0%.

3 business newspapers are each writing 8 stories about all these 8 events. You are going to be able to randomly pick and read 3 stories per newspaper. It is therefore unlikely that you will read about everything. Instead, you will probably read stories about the same event several times. But keep in mind that in this context, each event should have an equal importance for your decisions, no matter how many times it comes up in your choice of stories.
Experimental Design

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Mobius, Rosenblat and Vautrey (2019) The Role of Memory in Belief Formation
Experimental Design

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- We generate 8 news snippets with positive valence ("good news") or negative valence ("bad news").
- A well managed (poorly managed) Illustra produces good news with 70% probability (30% probability).
Experimental Design

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- Three newspapers are reporting these news stories.
- Participant can read 3 random snippets per newspaper.
- Probability that particular snippet is not read: \( \left( \frac{5}{8} \right)^3 = 0.244 \).
- On average, participants see 6 unique snippets and 3 repetitions.
Details: News Snippet Generation

- We start with a database of 20 descriptive events.
- For each participant, we select 8 out of these 20 events.
  - **Example:** *WTO agreement on copyright*
- Depending on Illustra’s type we assign a positive or negative valence to the event with the correct probability.
  - **Good news:** *Illustra’s CEO praised the successful conclusion of the WTO agreement on intellectual property right protection (..)*
  - **Bad news:** *Illustra’s CEO lamented the failure of the WTO agreement on intellectual property right protection (..)*
- The wording of the news event differs slightly across publications:

  Illustra condemned the failure of the WTO agreement on intellectual property rights protection. Illustra has criticized copycat producers in developing countries and accused them of free-riding on Illustra’s Research and Development. The CEO of Illustra stated that they had ‘high hopes’ for the WTO agreement and just announced their ‘disappointment’ at its failure.

  Illustra's CEO lamented the failure of the WTO agreement on intellectual property right protection. 'Copycat producers in developing countries free-ride on our research', the CEO said. 'We had high hopes on the WTO agreement. We are very disappointed that the agreement is shelved for good.'
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- The wording of the news event differs slightly across publications:

  By randomly assigning valence we ensure that the “average” strength of positive and negative signals is the same.
News reading phase: blurred snippets
News reading phase: blurred snippets

For each of the 3 newspapers, participant sees 8 blurred snippets.
Experimental Design

Newspapers: shuffling snippets

The Investor's Review
Wednesday, May 10th
Experimental Design

Newspapers: shuffling snippets

She has to explicitly shuffle the snippets.
Newspapers: chosen snippets

The Investor’s Review

Wednesday, May 19th

- Analysts predict that Asutra’s new multi-LCD screens will not be adopted by smartphones manufacturers until 2020 at the earliest due to high costs. MicroLED combines the longevity of traditional LCD technology with the perfect contrast of OLED technology. Asutra’s second generation screen technology may well have a strong shot at success.

- South American consumers will likely turn their backs on Asutra’s new-generation appliances. This is due to the fact that Asutra’s new assistant, which is being sold all over the world, is having serious problems with the Spanish language.

- Asutra will continue to edge their taxes in China for the next 10 years. Chinese authorities have cleared the company of accusations that it is not paying its fair share. Asutra has argued that its sales in the country should not be taxed because the majority of new products are located outside China. Local tax authorities have now accepted this argument.

Next
Experimental Design

Newspapers: chosen snippets

The Investor's Review

Wednesday, May 19th

Analysts predict that Illusra's new micro-LED screens will not be adopted by smartphone manufacturers until 2025 at the earliest due to high costs. Illusra's micro-LED combines the longevity of traditional LED technology with the perfect contrast of OLED technology. Illusra invented nearly all of this technology and might now have to write off its investments.

South American consumers will likely turn their back on Illusra's next-generation appliances. This is due to the fact that Illusra's new assistant, which is built into all new appliances, is having serious problems with the Spanish language.

Illusra will continue to use tax havens in China for the next 10 years. Chinese authorities have cleared the company of accusations that it is not paying its fair share. Illusra has argued that its sales in the country should not be taxed because the majority of revenues are located outside China. Local tax authorities have now accepted this argument.

She then uncovers 3 of the 8 snippets.
Belief Elicitation: first newspaper

What is the probability that Illustra is well-managed? First answer.

Remember that the computer randomly chose the quality of Illustra’s management to be either good or bad. If it’s well managed, every unique event that happened to Illustra was positive with probability 70.0% and negative with probability 30.0%; if it’s poorly managed, every unique event that happened to Illustra was positive with probability 30.0% and negative with probability 70.0%. Therefore if someone had access to very many unique news and read a majority of good news, for instance, they would be very confident that Illustra is well managed.

Now that you have seen some news, how likely do you think it is that Illustra is well-managed?

Earnings
You will answer this question 4 times in our study. To give you incentives to answer exactly what you believe, one of them will be randomly chosen and paid according to the following scheme.

Don’t worry about the math: to maximize your earnings, you should enter your best guess of the probability that Illustra is well-managed given the news that you have seen.
The computer will draw a number, P, randomly between 0 and 100 (uniformly). If P is below your selected answer, you will get $1.5 if Illustra is well managed and $0 otherwise. But if P is above your selected answer, you will enter a lottery with winning odds P: you will receive $1.5 with probability P and $0 otherwise.
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There is a % chance that Illustra is well-managed:

We elicit beliefs using lottery method after each newspaper.
Experimental Design

Details: Lottery Method

We first used the method in Mobius, Niederle, Niehaus and Rosenblat (2007):

- Participant compares two lotteries:
  - She is a paid prize if Illustra is well managed and 0 otherwise.
  - She is paid a prize with probability $P$.
- Participant can choose the cutoff $P$ where she prefers the lottery over Illustra.
- Her optimal response is to report beliefs truthfully.
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- Her optimal response is to report beliefs truthfully.

Method only requires monotonicity axiom: when comparing two binary lotteries over the same outcomes, subjects should prefer the lottery that pays the prize with higher probability.
What is the probability that Illustra is well-managed?

Some events might have appeared several times due to your choice of stories from the 3 newspapers but this does not make any event more important than another one. In fact, each newspaper wrote one story about each event.

Remember that the computer randomly chose the quality of Illustra’s management to be either good or bad. If it’s well managed, every unique event that happened to Illustra was positive with probability 70.0% and negative with probability 30.0%; if it’s poorly managed, every unique event that happened to Illustra was positive with probability 30.0% and negative with probability 70.0%. Therefore if someone had access to very many unique news and read a majority of good news, for instance, they would be very confident that Illustra is well managed.

Now that you have seen some news, how likely do you think it is that Illustra is well-managed?

Earnings
Don’t worry about the math: to maximize your earnings, you should enter your best guess of the probability that Illustra is well-managed given the news that you have seen.

The computer will draw a number, P, randomly between 0 and 100 (uniformly). If P is below your selected answer, you will get $1.5 if Illustra is well managed and $0 otherwise. But if P is above your selected answer, you will enter a lottery with winning odds P: you will receive $1.5 with probability P and $0 otherwise.

There is a □□□ □□□ % chance that Illustra is well-managed:
Belief Elicitation: second and third newspaper

What is the probability that Illustra is well-managed?

Some events might have appeared several times due to your choice of stories from the 3 newspapers but this does not make any event more important than another one. In fact, each newspaper wrote one story about each event.

Remember that the computer randomly chose the quality of Illustra’s management to be either good or bad. If it’s well managed, every unique event that happened to Illustra was positive with probability 70.0% and negative with probability 30.0%; if it’s poorly managed, every unique event that happened to Illustra was positive with probability 30.0% and negative with probability 70.0%. Therefore if someone had access to very many unique news and read a majority of good news, for instance, they would be very confident that Illustra is well managed.

Now that you have seen some news, how likely do you think it is that Illustra is well-managed?

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There is a 71% chance that Illustra is well-managed:

We remind subjects that repeated information does not make the facts more salient.
Recognition Task

Which facts have you read about?

You are now going to see a sequence of news in a short format. Some of them were reported about in the articles that you clicked, some are just made up. For each of them, you have to try and remember if it was in the news that you read, or not. The only thing that matters is whether you read about the fact or not, not how many times. For each news you will have three answer options: "I am sure I have read about this", "This seems familiar", "I don't remember reading about this".

Earnings
Your will answer this question 10 times in our study. To give you incentives to answer exactly what you believe, one of them will be randomly chosen. You bonus or penalty will depend on whether you actually clicked this news earlier and what was your answer on "Have you seen..." according to this table:

<table>
<thead>
<tr>
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<th>&quot;This seems familiar&quot;</th>
<th>&quot;I do not remember reading about this&quot;</th>
</tr>
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<tbody>
<tr>
<td>You clicked on this news before</td>
<td>$1 bonus</td>
<td>$0.5 bonus</td>
<td>$0</td>
</tr>
<tr>
<td>You did not click on this news before</td>
<td>$-0.5 penalty</td>
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Experimental Design

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We show subjects 10 snippets (including the eight ones selected for them plus 2 extra ones).
Recognition Task

Have you read about...

Illustra's CEO Tim Wilson is criticized for breaking his promise to direct 5% of company profits to underserved children education fund over the past 10 years.

I am sure I have read about this

This seems familiar

I do not remember reading about this

Next
Recognition Task

Have you read about...

_Illustra's CEO Tim Wilson is criticized for breaking his promise to direct 5% of company profits to underserved children education fund over the past 10 years._

I am sure I have read about this

This seems familiar

I do not remember reading about this

Subjects can answer with sure/unsure/not seen.
Empirical Model: Bayesian Updating

Bayes rule after seeing fact $s$ about Illustra:

$$
\text{Posterior} = \frac{\text{Illustra is H and fact } s}{\text{Illustra is type H and fact } s + \text{Illustra is type L and fact } s} \\
\mu_t = \frac{\mu_{t-1} F_H(s_t)}{\mu_{t-1} \cdot F_H(s_t) + (1 - \mu_{t-1}) \cdot F_L(s_t)}
$$

where $s_t \in \{H, L\}$.

This is equivalent to

$$
\logit(\mu_t) = \logit(\mu_{t-1}) + I(s_t = H) \lambda_H + I(s_t = L) \lambda_L
$$

where

- $\logit(\mu) = \log \left( \frac{\mu}{1 - \mu} \right)$ is the logit belief
Empirical Model: Bayesian Updating

Bayes rule after seeing fact $s$ about Illustra:

$$\text{Posterior} = \frac{\text{Illustra is H and fact } s}{\text{Illustra is type H and fact } s + \text{Illustra is type L and fact } s}$$

$$\mu_t = \frac{\mu_{t-1} F_H(s_t)}{\mu_{t-1} \cdot F_H(s_t) + (1 - \mu_{t-1}) \cdot F_L(s_t)}$$

where $s_t \in \{H, L\}$.

This is equivalent to

$$\logit(\mu_t) = \logit(\mu_{t-1}) + I(s_t = H)\lambda_H + I(s_t = L)\lambda_L$$

where

- $\logit(\mu) = \log \left( \frac{\mu}{1 - \mu} \right)$ is the logit belief
- $\lambda_H = \log \left( \frac{F_H(H)}{F_L(H)} \right) > 0$ is the LLR for a positive signal
Empirical Model: Bayesian Updating

Bayes rule after seeing fact \( s \) about Illustra:

\[
\text{Posterior} = \frac{\text{Illustra is H and fact } s}{\text{Illustra is type H and fact } s + \text{Illustra is type L and fact } s} \\
\mu_t = \frac{\mu_{t-1} F_H(s_t)}{\mu_{t-1} \cdot F_H(s_t) + (1 - \mu_{t-1}) \cdot F_L(s_t)}
\]

where \( s_t \in \{H, L\} \).

This is equivalent to

\[
\logit(\mu_t) = \logit(\mu_{t-1}) + I(s_t = H)\lambda_H + I(s_t = L)\lambda_L
\]

where

- \( \logit(\mu) = \log \left( \frac{\mu}{1-\mu} \right) \) is is the logit belief

- \( \lambda_H = \log \left( \frac{F_H(H)}{F_L(H)} \right) = \log \left( \frac{0.7}{0.3} \right) > 0 \) is the LLR for a positive signal

- \( \lambda_L = \log \left( \frac{F_H(L)}{F_L(L)} \right) = \log \left( \frac{0.3}{0.7} \right) < 0 \) is the LLR for a negative signal
Empirical Model: Linear Model

We obtain a linear empirical model:

$$\text{logit}(\hat{\mu}_i) = \alpha + \beta_H \cdot \{\# \text{ positive signals}\} \cdot \lambda_H + \beta_L \cdot \{\# \text{ negative signals}\} \cdot \lambda_L + \epsilon_i$$

- $\beta_H$ and $\beta_L$ capture responsiveness to positive and negative information
- Bayes rule implies $\alpha = 0$, $\beta_H = \beta_L = 1$. 
## Belief Regression: After First Newspaper

<table>
<thead>
<tr>
<th></th>
<th>Belief after First Newspaper</th>
</tr>
</thead>
<tbody>
<tr>
<td># Pos.</td>
<td>0.4089 (0.0338)</td>
</tr>
<tr>
<td># Neg.</td>
<td>-0.3214 (0.0342)</td>
</tr>
<tr>
<td>Observations</td>
<td>146</td>
</tr>
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</table>
Belief Regression: After First Newspaper

| # Pos. | 0.4089  
|       | (0.0338) |
| # Neg. | -0.3214  
|       | (0.0342) |

Observations 146

Subjects are more conservative than predicted by Bayesian updating.
Belief Regression: After Second Newspaper

<table>
<thead>
<tr>
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<th>(1) Belief after Second Newspaper</th>
</tr>
</thead>
<tbody>
<tr>
<td># (Pos. Unique)</td>
<td>0.2495 (0.0502)</td>
</tr>
<tr>
<td># (Pos. Repeated)</td>
<td>0.2508 (0.0533)</td>
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<tr>
<td># (Neg. Unique)</td>
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<tr>
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Repeated snippets are *not* double-counted.
## Belief Regression: After Third Newspaper

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<tbody>
<tr>
<td># (Pos. Unique)</td>
<td>0.2510 (0.0388)</td>
</tr>
<tr>
<td># (Pos. Repeated)</td>
<td>0.2258 (0.0559)</td>
</tr>
<tr>
<td># (Neg. Unique)</td>
<td>-0.1329 (0.0347)</td>
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<tr>
<td># (Neg. Repeated)</td>
<td>-0.3256 (0.0609)</td>
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## Belief Regression: After Third Newspaper

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Final beliefs show slight double-counting for negative signals.
Belief Regression: After Third Newspaper

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<td># (Pos. Unique Unrecognized)</td>
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<td># (Pos. Repeated Recognized)</td>
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<tr>
<td># (Pos. Repeated Unrecognized)</td>
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</tr>
<tr>
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<td>(0.1962)</td>
</tr>
<tr>
<td># (Neg. Unique Recognized)</td>
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</tr>
<tr>
<td></td>
<td>(0.0411)</td>
</tr>
<tr>
<td># (Neg. Unique Unrecognized)</td>
<td>-0.1716</td>
</tr>
<tr>
<td></td>
<td>(0.0814)</td>
</tr>
<tr>
<td># (Neg. Repeated Recognized)</td>
<td>-0.2818</td>
</tr>
<tr>
<td></td>
<td>(0.0653)</td>
</tr>
<tr>
<td># (Neg. Repeated Unrecognized)</td>
<td>-0.5432</td>
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<td>(0.1712)</td>
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Double-counting originates mostly from unrecognized signals.

Mobius, Rosenblat and Vautrey (2019)
## Belief Regression: After Third Newspaper

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Double-counting originates mostly from *unrecognized* signals.
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<tr>
<td>Constant</td>
<td>0.7392 (0.0214)</td>
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<tr>
<td>Positive</td>
<td>0.0197 (0.0096)</td>
</tr>
<tr>
<td>Repeated</td>
<td>0.1310 (0.0200)</td>
</tr>
<tr>
<td>Time on News Page</td>
<td>0.0003 (0.0002)</td>
</tr>
<tr>
<td>Time on Recognition Page</td>
<td>-0.0011 (0.0006)</td>
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<tr>
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Note: Includes participant fixed effects.
## Fact-level Regression

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Recognition increases by 13pp from 74% to 87% when signals are repeated.
## Fact-level Regression

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Note: Includes fact ID and participant fixed effects.
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Note: Includes fact ID and participant fixed effects.

Other covariates have no significant effect on recognition.
Extension: The Effect of Time on Memory

Participants are asked to perform a filler task (5 minute Raven test):

- Control group has filler task at the very end after recognition phase.
- Treatment A performs filler before recognition phase.
- Treatment B performs filler before final belief elicitation.
Extension: The Effect of Time on Memory

Participants are asked to perform a filler task (5 minute Raven test):

- Control group has filler task at the very end after recognition phase.
- Treatment A performs filler before recognition phase.
- Treatment B performs filler before final belief elicitation.

Treatment A allows us to explore how recognition decays over time and treatment B allows us to explore its effect on beliefs.
Extension: Social Learning

Two participants are asked to learn half the signals about two events.

- They are invited to communicate in free form.
- We elicit beliefs and test recognition across all facts (both own and those by partner).
Extension: Social Learning

Two participants are asked to learn half the signals about two events.

- They are invited to communicate in free form.
- We elicit beliefs and test recognition across all facts (both own and those by partner).

- We expect that recall is relatively more important for social learning compared to recognition (because a memory hash function cannot be communicated).

- Prior research has shown that social learners generally underweigh the information of others by a factor of 2 (in terms of effect on logit beliefs).
Extension: Motivated Bias

Participant are given a “stake” in Illustra’s success.

- Treatment group gets a stake in Illustra’s success ⇒ subjects with belief utility have an incentive to apply a motivated bias in their beliefs.
- Control group has no stake.
Extension: Motivated Bias

Participant are given a “stake” in Illustra’s success.

- Treatment group gets a stake in Illustra’s success ⇒ subjects with belief utility have an incentive to apply a motivated bias in their beliefs.
- Control group has no stake.

Subjects might implement motivated biases by manipulating their memory (recognition).
Conclusion

1. We propose an experimental design that allows us to explore biases in belief updating based on signal processing.
   - By abstracting away from processing posterior beliefs (as in the correlated beliefs literature) we can use insights from cognitive psychology and treat signals as memories.

2. Recognized signals affect beliefs strongly and exhibit little double-counting.

3. Unrecognized signals affect beliefs weakly and exhibit strong double-counting.