A biased tour of the uncertainty visualization zoo

Matthew Kay
Assistant Professor
School of Information
University of Michigan
[courtesy Xiaoying Pu, Puhe Liang]
What happens when we ignore uncertainty?
A mixed-design ANOVA with sex of face (male, female) as a within-subjects factor and self-rated attractiveness (low, average, high) and oral contraceptive use (true, false) as between-subjects factors revealed a main effect of sex of face, $F(1, 1276) = 1372$, $p < .001$, $\eta^2_p = .52$. This was qualified by interactions between sex of face and SRA, $F(2, 1276) = 6.90$, $p = .001$, $\eta^2_p = .011$, and between sex of face and oral contraceptive use, $F(1, 1276) = 5.02$, $p = .025$, $\eta^2_p = .004$. The predicted interaction among sex of face, SRA and oral contraceptive use was not significant, $F(2, 1276) = 0.06$, $p = .94$, $\eta^2_p < .001$. All other main effects and interactions were non-significant and irrelevant to our hypotheses, all $F \leq 0.94$, $p \geq .39$, $\eta^2_p \leq .001$. 
A mixed-design ANOVA with sex of face (male, female) as a within-subjects factor and self-rated attractiveness (low, average, high) and oral contraceptive use (true, false) as between-subjects factors revealed a main effect of sex of face, $F(1, 1276) = 1372, p < .001, \eta^2_p = .52$. This was qualified by interactions between sex of face and SRA, $F(2, 1276) = 6.90, p = .001, \eta^2_p = .011$, and between sex of face and oral contraceptive use, $F(1, 1276) = 5.02, p = .025, \eta^2_p = .004$. The predicted interaction among sex of face, SRA and oral contraceptive use was not significant, $F(2, 1276) = 0.06, p = .94, \eta^2_p < .001$. All other main effects and interactions were not significant and irrelevant to our hypotheses, all $F \leq 0.02, p \geq .39, \eta^2_p \leq .001$. 
# Alternatives...

Table 7
Stevens et al. 2006, table 2: Determinants of authoritarian aggression

<table>
<thead>
<tr>
<th>Variable</th>
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<td>Constant</td>
<td>.41 (.90)</td>
</tr>
<tr>
<td>Countries</td>
<td></td>
</tr>
<tr>
<td>Argentina</td>
<td>.51 (.30)**</td>
</tr>
<tr>
<td>Chile</td>
<td>-.92 (.29)*</td>
</tr>
<tr>
<td>Colombia</td>
<td>.14 (.32)*</td>
</tr>
<tr>
<td>Mexico</td>
<td>.07 (.30)</td>
</tr>
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<tr>
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</tr>
<tr>
<td>Retrospective egocentric economic perceptions</td>
<td>.20 (13)</td>
</tr>
<tr>
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<td>.22 (12)*</td>
</tr>
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<td>-.21 (12)*</td>
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<td>Individual Differences</td>
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</tr>
<tr>
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</tr>
<tr>
<td>R²</td>
<td>.15</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>.12</td>
</tr>
<tr>
<td>N</td>
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*"p < .01; "p < .05; "p < .10 (uncorrected).
*Coefficient is significantly different from Argentinians at p < .05.
*Coefficient is significantly different from Brazil’s at p < .05.
*Coefficient is significantly different from Chile’s at p < .05.
*Coefficient is significantly different from Colombia’s at p < .05.
*Coefficient is significantly different from Mexico’s at p < .05.
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Altneratives...

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\(p<.05\) indicates statistical significance.

3. We estimate the ratio of average JNDS between successive groups over all values of r from 0.3 to 0.8.

The low precision group is between 1.5 and 3 times more precise than the chance group.

The high precision group is between 1.5 and 2 times more precise than the medium precision group.

How easy is it to ignore the uncertainty?

This contributes to dichotomania
### Predictions from 2016 presidential election


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Predictions from 2016 presidential election

People are very good at ignoring uncertainty...
People are very good at ignoring uncertainty...

Especially when we provide bad uncertainty representations
Icon arrays in medical risk communication

(Figure from Fagerlin, Wang, Ubel. Reducing the influence of anecdotal reasoning on people’s health care decisions: Is a picture worth a thousand statistics? Medical Decision Making 2005; 25:398–405)
What is an icon array for a continuous distribution?
What is an icon array for a continuous distribution?

An example scenario...
28
BROADVIEW
11:09 - on time

16
NORTHGATE
11:10 - on time

358E
AURORA VILLAGE
11:12 - on time

120
DOWNTOWN
11:15 - 6 min delay

5
NORTHGATE
11:17 - 3 min delay

Be advised:
Bus arrival estimates are based on the best available information but actual times will vary. Traffic and other conditions can affect the accuracy of this information.

SDOT OneBusAway King County
<table>
<thead>
<tr>
<th>Route</th>
<th>Destination</th>
<th>Time</th>
<th>Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>358E</td>
<td>5 BROADVIEW FREMONT</td>
<td>11:05 on time</td>
<td>8 min delay</td>
</tr>
<tr>
<td>16</td>
<td>6 NORTHGATE WALLINGFORD</td>
<td>11:10 on time</td>
<td></td>
</tr>
<tr>
<td>358E</td>
<td>8 AURORA VILLAGE VIA AURORA AVE N</td>
<td>11:12 on time</td>
<td></td>
</tr>
<tr>
<td>120</td>
<td>11 DOWNTOWN SEATTLE WHITE CENTER</td>
<td>11:15</td>
<td>6 min delay</td>
</tr>
<tr>
<td>5</td>
<td>13 NORTHGATE GREENWOOD</td>
<td>11:17</td>
<td>3 min delay</td>
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Be advised:

Bus arrival estimates are based on the best available information but actual times will vary. Traffic and other conditions can affect the accuracy of this information.
Do I have time to get a coffee?
11 min
Minutes until bus arrives

11 min
90% chance the bus comes at ~8 min or later.
11 min

5 10 15 20 25 30

Minutes until bus arrives

~8 min

11 min

~8 min

90% chance the bus comes at ~8 min or later
Minutes until bus arrives
Cumulative distribution function

Cumulative probability

Minutes until bus arrives
18/20 = 90% chance the bus comes at ~8 min or later
Quantile dotplots

Kay, Kola, Hullman, Munson. When (ish) is My Bus? User-centered Visualizations of Uncertainty in Everyday, Mobile Predictive Systems. CHI 2016

Better estimates
(perceptually)
Quantile dotplots

Better estimates (perceptually)
↓?
better decisions

Better estimates (perceptually)
↓?
better decisions

Error in estimated probability:
\[ \text{logit(estimated } p) - \text{logit(true } p) \]

Estimated \( p \) if true \( p \) was 0.5
Quantile dotplots

[Fernandes, Munson, Hullman, Kay. Uncertainty Displays Using Quantile Dotplots or CDFs Improve Transit Decision-Making. CHI 2018]

Better estimates (perceptually)

↓

better decisions (in this case)
**Quantile dotplots**

![Quantile dotplot graph](image)

- Better estimates (perceptually)
- \[\downarrow\]
- better decisions (in this case)

---

[Fernandes, Munson, Hullman, Kay. Uncertainty Displays Using Quantile Dotplots or CDFs Improve Transit Decision-Making. CHI 2018]
(Sidebar —

**Uncertainty**: what am I talking about?)
For the purposes of this talk...

I am largely adopting a **Bayesian** view of uncertainty

Put another way: **uncertainty is probability**
Data

−4 −6 −2 0 2 4 6 8 10 12 B – A (difference in seconds)

A is faster   B is faster

Data

A − B (difference in seconds)
I want: \( P(\text{mean difference} \mid \text{data}) \)
I want: \( P(\text{mean difference} \mid \text{data}) \)
I want: $P(\text{mean difference} \mid \text{data})$
I want: $P(\text{mean difference} \mid \text{data})$
I want: \[ P(\text{mean difference} \mid \text{data}) \]

\[ P(\text{data} \mid \text{mean difference} = x) \]
I want: \( P(\text{mean difference} \mid \text{data}) \)

\( P(\text{data} \mid \text{mean difference} = x) \)
I want: \( P(\text{mean difference} \mid \text{data}) \)

\[
\text{Likelihood} = P(\text{data} \mid \text{mean difference})
\]
I want: \( P(\text{mean difference} \mid \text{data}) \)

Likelihood = \( P(\text{data} \mid \text{mean difference}) \)
Data

−4 −6 −2 0 2 4 6 8 10 12

B is faster
A is faster

I want: \( P(\text{mean difference} \mid \text{data}) \)

Prior = \( P(\text{mean difference}) \)

Likelihood = \( P(\text{data} \mid \text{mean difference}) \)

Frequentist estimate

Data

A − B (difference in seconds)
I want: \[ P(\text{mean difference} \mid \text{data}) \propto \text{Likelihood} \times \text{Prior} \]

Prior = \[ P(\text{mean difference}) \]

Likelihood = \[ P(\text{data} \mid \text{mean difference}) \]

Frequentist estimate

Data

A − B (difference in seconds)
I want: \[ P(\text{mean difference} | \text{data}) \propto \text{Likelihood} \times \text{Prior} \]

Prior = \[ P(\text{mean difference}) \]

Likelihood = \[ P(\text{data} | \text{mean difference}) \]
Data

\[ \begin{align*}
-4 & \quad -6 & \quad -2 & \quad 0 & \quad 2 & \quad 4 & \quad 6 & \quad 8 & \quad 10 & \quad 12 \\
B - A & \text{ (difference in seconds)} \\
\end{align*} \]

\[
B \text{ is faster} \quad \quad A \text{ is faster}
\]

Bayesian estimate

\[
P(\text{mean difference} | \text{data}) \propto \text{Likelihood} \times \text{Prior}
\]

Frequentist estimate

\[
P(\text{mean difference})
\]

I want:

\[
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\[
\text{Prior} = P(\text{mean difference})
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\[
\text{Likelihood} = P(\text{data} | \text{mean difference})
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\[
A - B \text{ (difference in seconds)}
\]
I want: \( P(\text{mean difference} \mid \text{data}) \propto \text{Likelihood} \times \text{Prior} \)

Prior = \( P(\text{mean difference}) \)

Likelihood = \( P(\text{data} \mid \text{mean difference}) \)

Bayesian estimate

Frequentist estimate

Data

A − B (difference in seconds)
Bayesian estimate

$$P(\text{mean difference} \mid \text{data}) \propto \text{Likelihood} \times \text{Prior}$$

Prior = $P(\text{mean difference})$

Likelihood = $P(\text{data} \mid \text{mean difference})$

I want: $P(\text{mean difference} \mid \text{data})$

Posterior = $P(\text{mean difference} \mid \text{data}) \propto \text{Likelihood} \times \text{Prior}$

Posterior sample

Bayesian estimate

Frequentist estimate

Data

$A - B$ (difference in seconds)
I want:

\[ P(\text{mean difference} | \text{data}) \propto \text{Likelihood} \times \text{Prior} \]

Prior =

\[ P(\text{mean difference}) \]

Likelihood =

\[ P(\text{data} | \text{mean difference}) \]

Posterior =

\[ P(\text{mean difference} | \text{data}) \]

Posterior sample

Bayesian estimate

Frequentist estimate

Data

\[ A - B \text{ (difference in seconds)} \]
For the purposes of this talk...

I am largely adopting a Bayesian view of uncertainty.

Put another way: uncertainty is probability.
(End sidebar —
Back to uncertainty vis)
Discrete outcome / frequency framing

Success Rate of Balloon Angioplasty

- Successfully cured of angina
- Not successfully cured of angina

Minutes until bus arrives

0 5 10 15 20

Quantile dotplot
## Predictions from 2016 presidential election


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FiveThirtyEight’s new House forecast

[https://projects.fivethirtyeight.com/2018-midterm-election-forecast/house/]

7 in 9
Chance Democrats win control (77.5%)

2 in 9
Chance Republicans keep control (22.5%)

Breakdown of seats by party:
- 267 D
- 108 R
- 247 D
- 208 R
- 227 D
- 208 R
- 227 R
- 208 D
- 247 R
- 168 D

Higher probability

10% chance Democrats gain more than 56 seats
80% chance Democrats gain 16 to 56 seats
10% chance Democrats gain fewer than 16 seats

+35 Democratic seats
+56 AVG. GAIN
+16
FiveThirtyEight's new House forecast

7 in 9
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Breakdown of seats by party
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Higher probability

+56
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7 in 9
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2 in 9
Chance Republicans keep control (22.5%)

Breakdown of seats by party:
- 287 D
- 168 R
- 247 D
- 208 R
- 227 D
- 208 R
- 227 R
- 208 D
- 247 R
- 168 D

Current breakdown:
- +56
+35 Democratic seats
AVG. GAIN
+16

10% chance Democrats gain more than 56 seats
80% chance Democrats gain 16 to 56 seats
10% chance Democrats gain fewer than 16 seats
Other **discrete outcome** uncertainty visualizations...
5. RESULTS

Figure 10 shows each of the six cases presented to the experiment participants, in their order of presentation, with the top row of each case showing the error cone view, and the bottom row showing our method. These examples were

![Image of hurricane error cones](image-url)

**FIG. 10:** The six cases as shown to experiment participants.
Hurricane error cones

(but problems with ensembles...)

(but problems with ensembles...)  

Deterministic construal errors

Deterministic construal errors


5. RESULTS

Figure 10 shows each of the six cases presented to the experiment participants, in their order of presentation, with the top row of each case showing the error cone view, and the bottom row showing our method. These examples were:

Case 1 Case 2 Case 3
Case 4 Case 5 Case 6

FIG. 10: The six cases as shown to experiment participants.
Deterministic construal errors

Fit line uncertainty
Fit line uncertainty
Fit line uncertainty

HOPs might aid deterministic construal errors
HOPs might aid deterministic construal errors
Hurricane location at a time slice...

[Liu, Boone, Ruginski, Padilla, Hegarty, Creem-Regehr, ... House. Uncertainty Visualization by Representative Sampling from Prediction Ensembles. IEEE Transactions on Visualization and Computer Graphics, PP(99), 2016]
Hurricane location at a time slice...

[Liu, Boone, Ruginski, Padilla, Hegarty, Creem-Regehr, ... House. Uncertainty Visualization by Representative Sampling from Prediction Ensembles. IEEE Transactions on Visualization and Computer Graphics, PP(99), 2016]
Animated uncertainty is showing up in the media...
Jobs report (NYT)

[Irwin & Quealy, How Not to Be Misled by the Jobs Report, NYT The Upshot, 2014, https://nyti.ms/RyZB8a]

If job growth **were actually steady** over the last 12 months...

...the jobs report **could look like this:**
Turn out this actually works!


If job growth were actually steady over the last 12 months...

...the jobs report could look like this:
Measles vaccination

Animation helps people experience uncertainty. This can be very powerful...
Income of black boys from wealthy families

[Badger, Miller, Pearce, Quealy. Extensive Data Shows Punishing Reach of Racism for Black Boys, NYT Upshot, 2018, https://nyti.ms/2GGpFZw]

Most white boys raised in wealthy families will stay rich or upper middle class as adults, but black boys raised in similarly rich households will not.
Cartographic uncertainty
Just map to another visual channel, right?

Just map to another visual channel, right?

Just map to another visual channel, right?


Very abstract…
Glyph-based uncertainty


Color saturation

Blur

Blur

More uncertainty
Glyph-based uncertainty


Color saturation

Blur

More intuitive?
But how accurate?

More uncertainty
I'm not a GIS person, so let's take a little detour
...and back to map-land
Uncertainty $\rightarrow$ \textcolor{green}{dither} (samples from dist)

Uncertainty $\rightarrow$ ~**dither** (samples from dist)

Uncertainty -> \textit{dither} (samples from dist)


- Discrete outcomes
- Maybe more intuitive, maybe less?
- Possible \textit{deterministic construal errors}
Addressing bias in perception of probability...
Value-suppressing uncertainty palettes

[Correll, Moritz, Heer. Value-Suppressing Uncertainty Palettes. CHI 2018]
Linear-in-log-odds perception of proportions

[Zhang & Maloney. Ubiquitous log odds: A common representation of probability and frequency distortion in perception, action, and cognition. Frontiers in Neuroscience, 6(JAN), 1–14, 2012]
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[Zhang & Maloney. Ubiquitous log odds: A common representation of probability and frequency distortion in perception, action, and cognition. Frontiers in Neuroscience, 6(JAN), 1–14, 2012]
Going back to election data...
New York Times Election Needle

The Fake Twitchy Hell Dials of the New York Times’ Forecast Only Made Last Night Worse

By Jake Swearingen

Chance of Winning Presidency

Around 9:30 last night, this tweet popped up on my timeline:

stop tweeting the fucking hell dial

— Ericlimer (@ericlimer) November 9, 2016
But shouldn’t anxiety be proportional to uncertainty?
Uncertainty visualization as a moral imperative

We should...

present well-calibrated uncertainty that cannot be ignored in ways people can actually understand
Thanks!

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http://mjskay.github.io/tidybayes/
http://github.com/mjskay/uncertainty-examples

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Epistemic uncertainty  Aleatory uncertainty