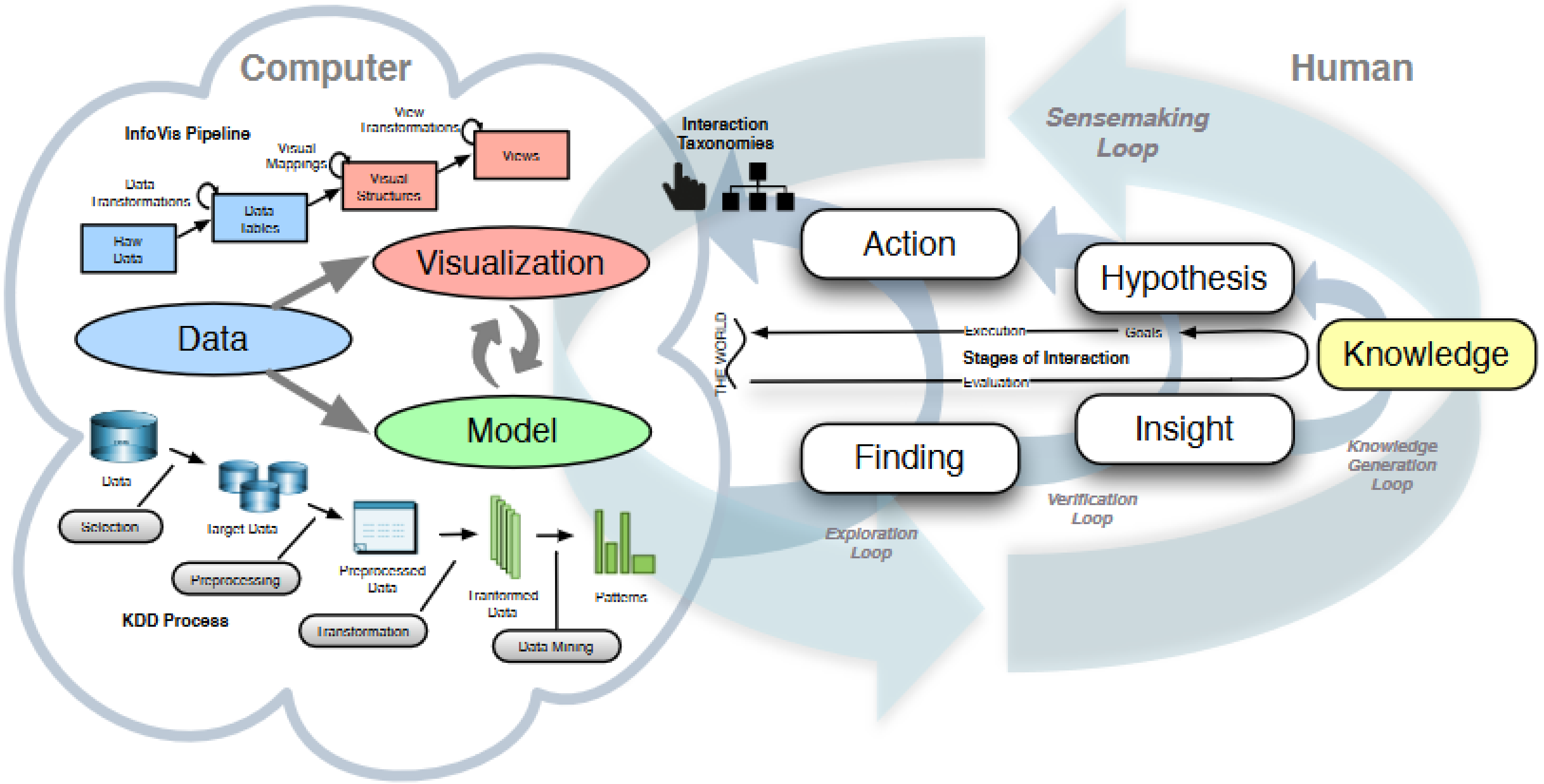
Visual Analytics, Machine Learning and Algorithmic Aversion

Ross Maciejewski, Arizona State University

Visual Analytics and the Human-in-the-Loop

- Visual analytics uses advanced analytical algorithms combined with interactive visual interfaces in which the user can explore the data and analyses
- This allows for the combination of domain expert knowledge with advanced analytics and data exploration



D. Sacha, A. Stoffel, F. Stoffel, B.C. Kwon, G. Ellis, D.A. Keim, “Knowledge Generation Model for Visual Analytics,” *IEEE Transactions on Visualization and Computer Graphics,*

VIS 2017

An Example of Success in Machine Learning

- In one example[1] of machine learning applications in medicine, scientists experimented with how machine learning might facilitate diagnosis of diabetic retinopathy, a condition that causes vision impairment and blindness. The team trained the system using 128,000 images of healthy eyes. They then had the algorithm analyze 12,000 images and graded its ability to recognize signs of disease. The results indicated that the system "matched or exceeded the performance of experts in identifying the condition and grading its severity."

1 - V. Gulshan, L. Peng, M. Coram, et al., "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs," *JAMA*, 2016;316(22):2402-2410

Machine Learning and Visual Analytics

- "Computation and analyses are often seen as black boxes that take tables as input and output, along with set of parameters, and run to completion or error without interruption"[1]

- "… calls for more research [...] on designing analysis modules that can repair computations when data changes, provide continuous feedback during the computation, and be steered by user interaction when possible"[1]

1 J.-D. Fekete. Visual Analytics Infrastructures: From Data Management to Exploration. Computer, 46(7):22–29, 2013

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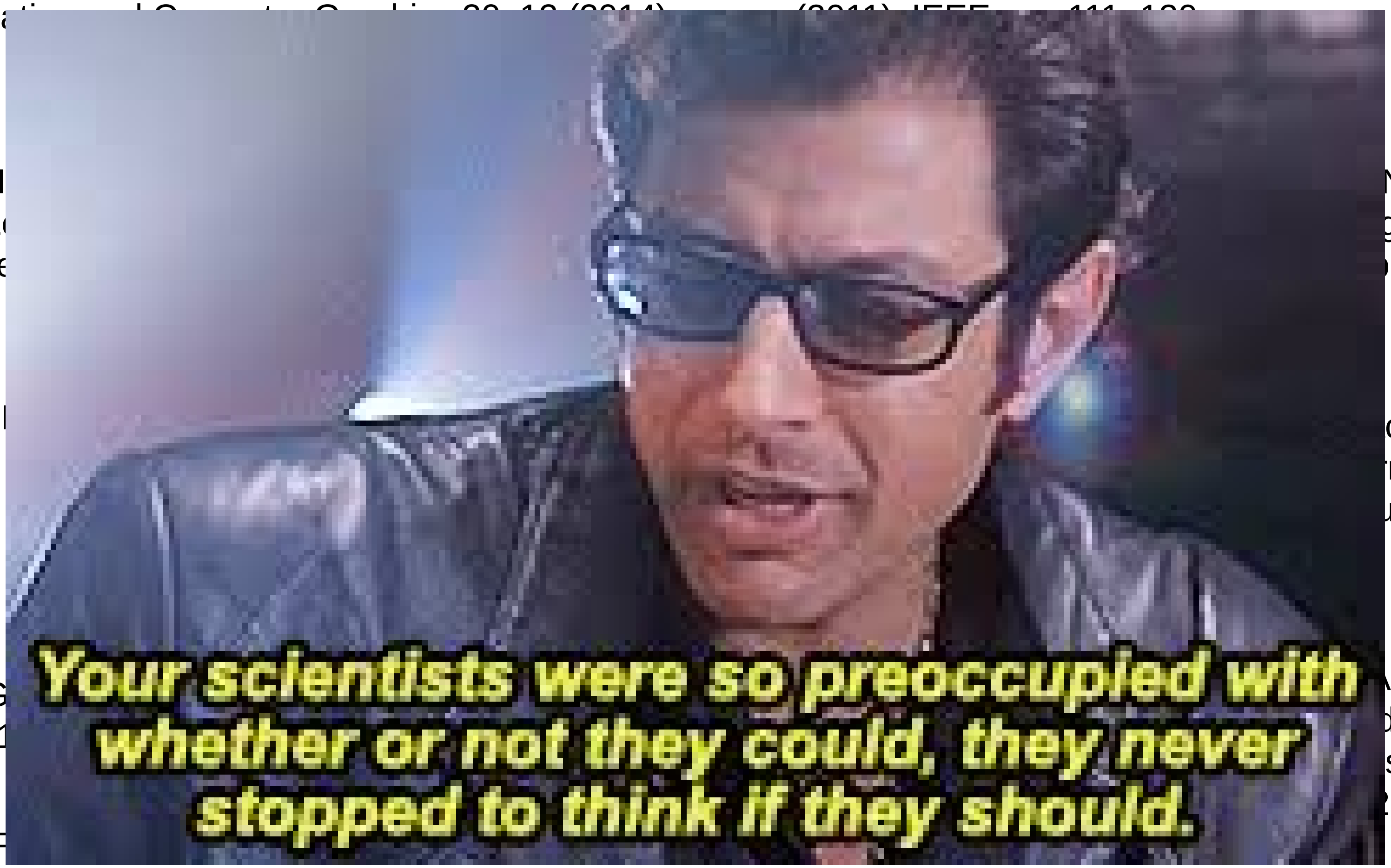

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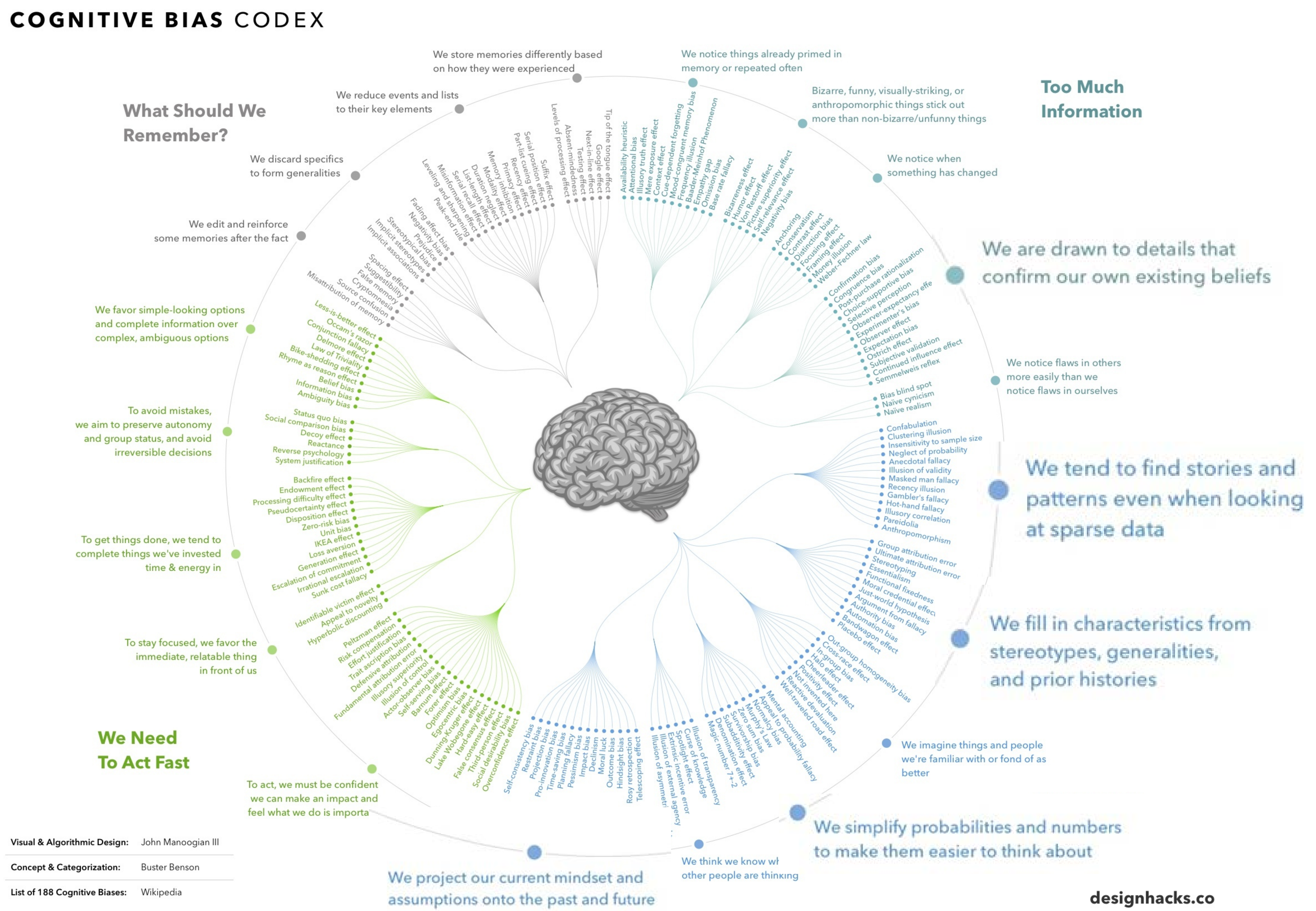

http://www.visualcapitalist.com/wp-content/uploads/2017/09/cognitive-bias-infographic.html

Humans-in-the-Loop?

- By giving users the option to integrate their domain knowledge, we have also allowed them to inject bias into the model.
- What’s the point of using technology to learn something new when you are bending it to fit your pre-existing notions?

Humans and Models

Users worsened the model's prediction[1].

Use their own prediction
Use model's prediction
Modify model's prediction

Allow users to adjust model's prediction

Model accuracy is higher (off by 17.5 percentiles on average)

1 - B. J. Dietvorst, J. P. Simmons, and C. Massey. Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. Management Science, 2016.

2 - Robyn M. Dawes. 1979. The robust beauty of improper linear models in decision making. *American Psychologist*, 34(7): 571-582

3 - Robyn M. Dawes, David Faust, and Paul E. Meehl. 1989. Clinical versus actual judgment. *Science* 243(4899): 1668-2674.

4 - William M. Grove, David H. Zald, Boyd S. Lebow, Beth E. Snitz, and Chad Nelson. 2000. Clinical versus mechanical prediction: A meta-analysis. *Psychological Assessment*, 12(1): 19-30.

5 - Nate Silver. 2012. *The signal and the noise: Why so may predictions fail-but some don't.* Penguin.

Algorithmic Aversion

- You'd think after years of using Google Maps we'd trust that it knows what it's doing. Still, we think, "Maybe taking the backroads would be faster."[1]
- People are even less trusting of algorithms if they've seen them fail, even a little. And they're harder on algorithms in this way than they are on other people.[2,3]
- An underlying goal of many visual analytics methods is to inject domain knowledge into the analysis and point out potential algorithmic errors to the end user for updating and correction.
- Visual analytics could potentially contribute to algorithmic aversion during forecasting tasks and lead to reduced performance.

1 - Walter Frick. Here's Why People Trust Human Judgment Over Algorithms. *Harvard Business Review.* February 27, 2015. https://hbr.org/2015/02/heres-why-people-trust-human-judgment-over-algorithms
2 – Berkeley J Dietvorst. 2016. People Reject (Superior) Algorithms Because They Compare Them to Counter-Normative Reference Points. 2016. https://ssrn.com/abstract=2881503
3 – Berkeley J Dietvorst, Joseph P. Simmons, and Cade Massey. 2015. Algorithm Aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General* 144(1): 114-126.

How far do you see the application of the human-in-the-loop paradigm within data visualization research threatened by the recent machine learning advances?

- **Domain Knowledge Integration** - There domains where human background knowledge is essential and where a lot of tacit knowledge which is difficult to represent in an algorithm plays a role. In such a case the human-in-the-loop approach may yield much better results.[1]
- **Visualization for Trust** - Studies report that forecasters may desire to adjust algorithmic outputs to gain a sense of ownership of the forecasts due to a lack of trust in statistical models.[2]
- **Visualization and Learning** - Typically that type of system means that the user will have some interactions that change a model, whether directly or indirectly. Getting engagement like that may really change the landscape of participation. It changes the idea of accuracy that you can test because the accuracy will evolve based on the human.

- **How can we regulate the knowledge integration so that we get the benefits of user knowledge and social and emotional intuition while minimizing the costs of introducing bias?**

1 - Research has shown that domain expertise diminished people's reliance on algorithmic forecasts which led to a worse performance. (Hal R Arkes, Robyn M Dawes, Caryn Christensen. 1986. Factors Influencing the Use of a Decision Rule in a Probabilistic Task. *Organizational Behavior and Human Decision Processes*. 37(1):93-110)
2 - Berkeley J. Dietvorst, Joseph P Simmons, and Cade Massey. 2016. Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. *Management Science.*