

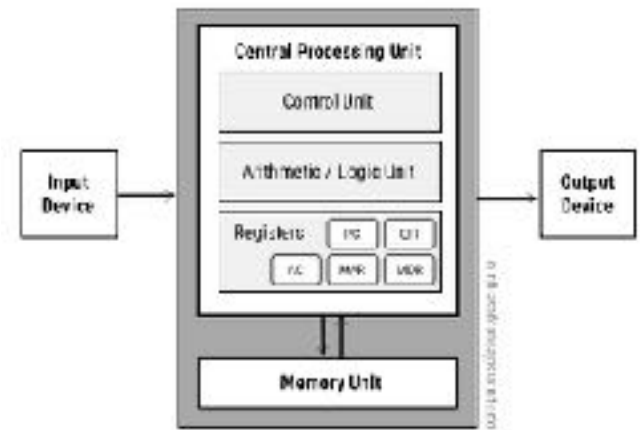
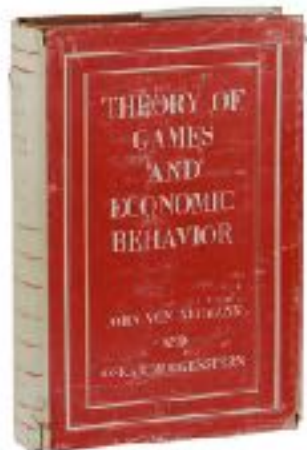
Prediction and Judgment

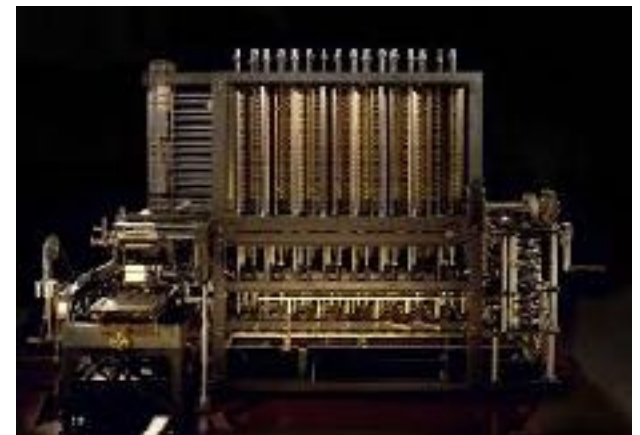
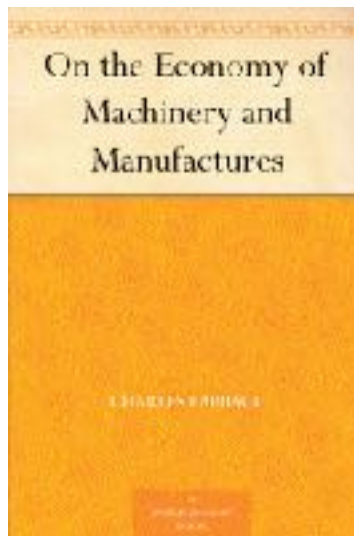
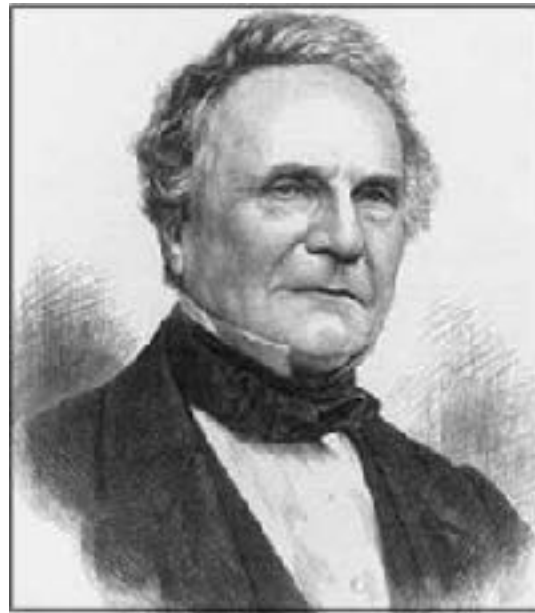
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Set of N tasks for a worker with element n

Works for T periods; uncertain of optimal task in each period

Complete contract: specify wage for each task in each period

$$\max_{\{n,t\}} E[F(n,t) - C(n,t)]$$

Employment contract: specify wage independent of task

$$\max_{\{n,t\}} E[F(n,t)]$$

Optimal to **limit** set of tasks that can be chosen in the employment contract

Recent AI is all about **prediction**


$$\max_{x \in X} \int u(x, \theta) dF(\theta | s)$$

Root of all worry



You seem to be using e-mail which
I know can't hold data on your
collusion with Russia.
Would you like to stop or are you
a fucking idiot?

Recent AI is all about **prediction**

$$\max_{x \in X} \int u(x, \theta) dF(\theta | s)$$


Where does this come from?

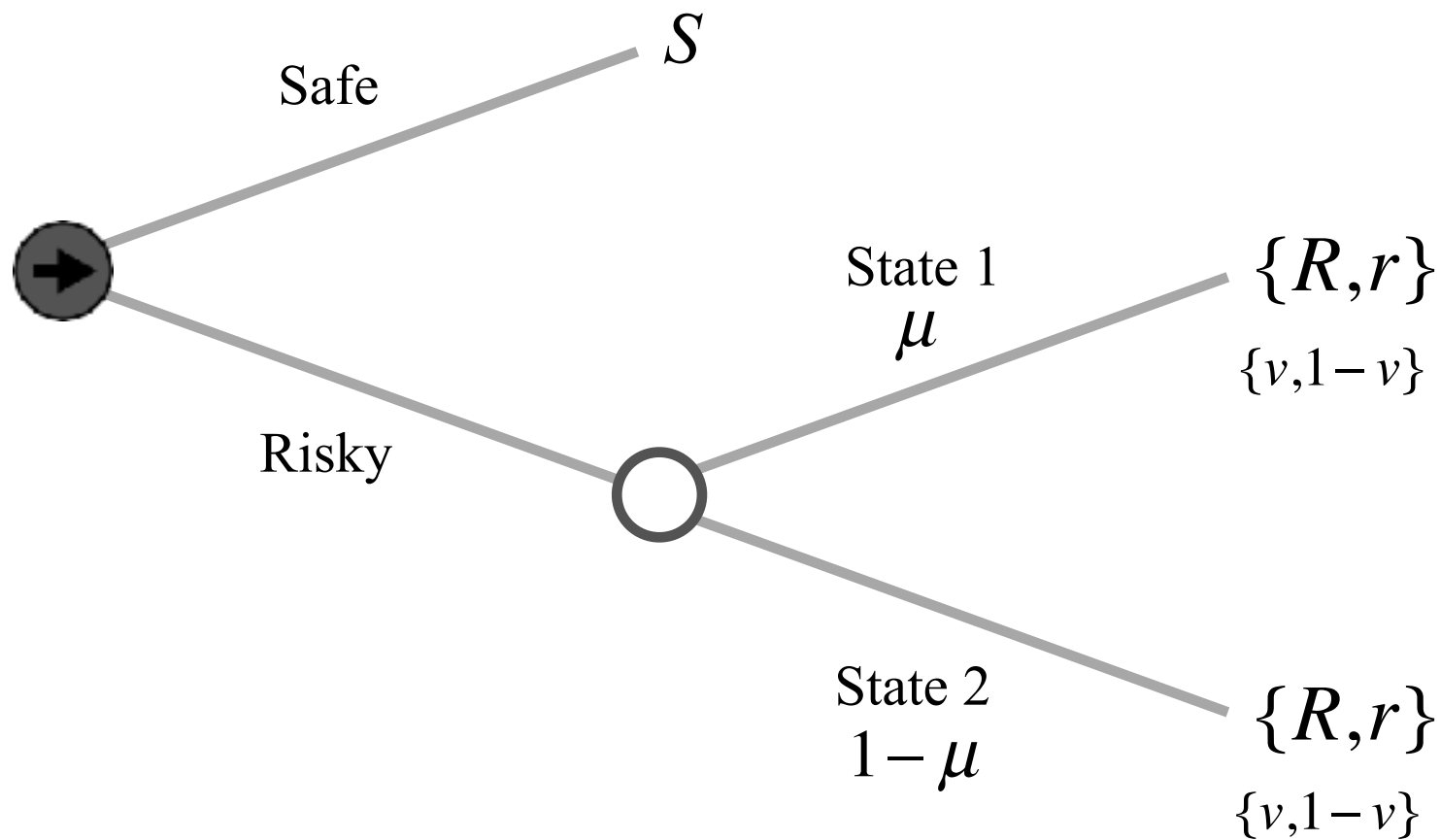
Thought

Experience

De gustibus non est disputandum

Judgment is the process of determining the value of actions in a given state

$$R > S > r$$



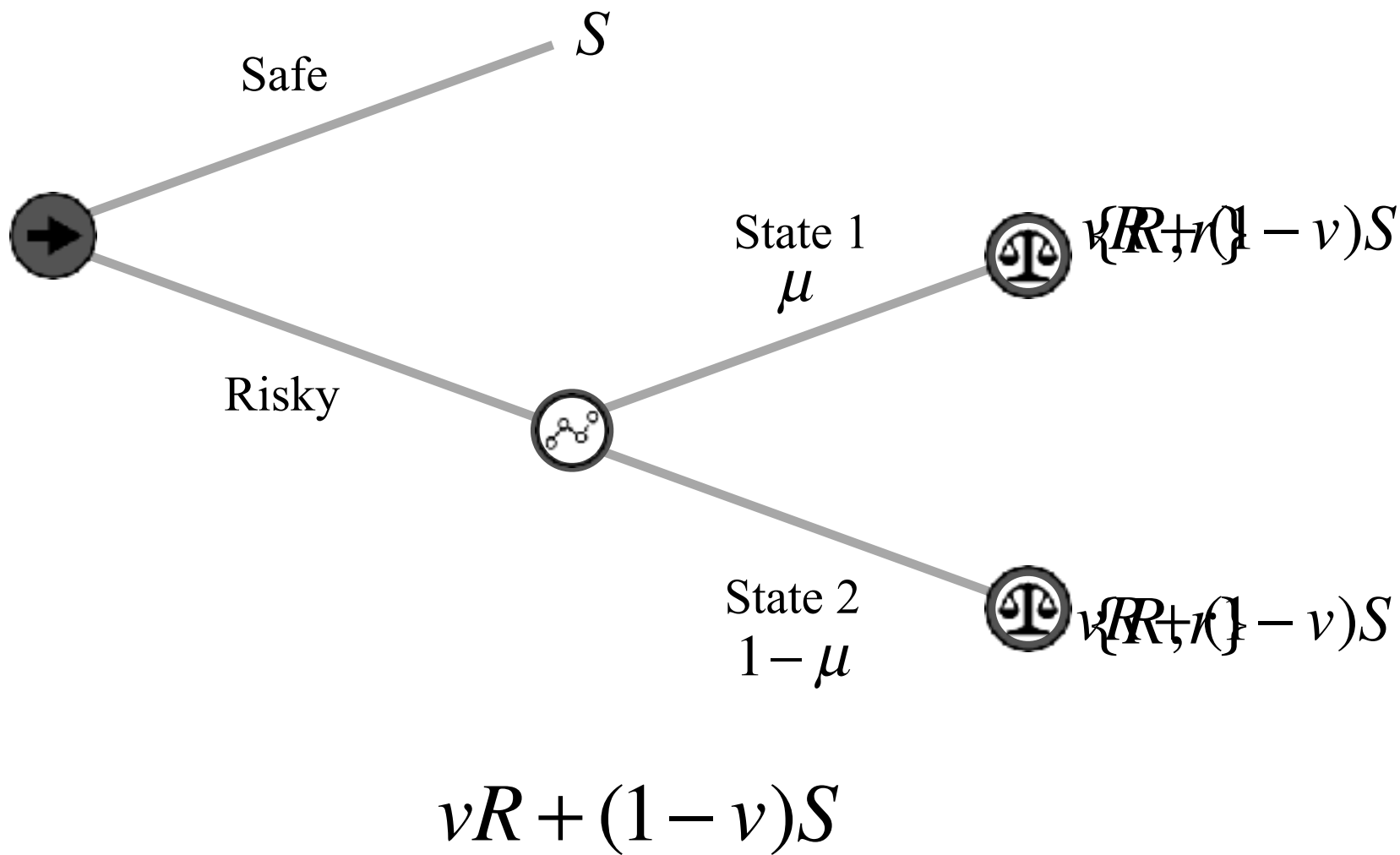
Are prediction and judgment complements or substitutes?

Simple intuition:

- If do not know the payoff, then knowing the state is not valuable
- If do not know the state, then knowing the payoff is not valuable

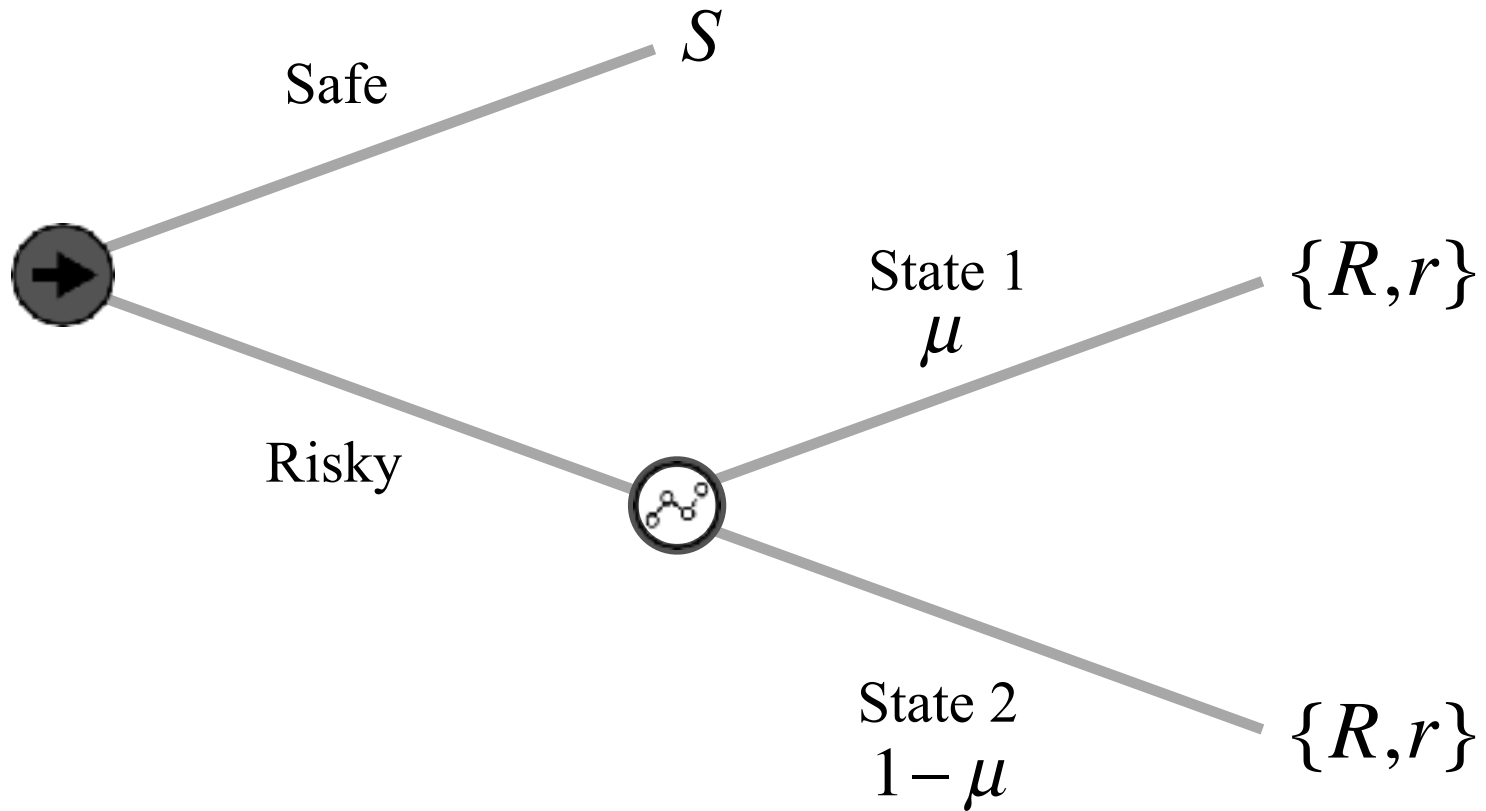
Complements
(not quite true)

What happens if you have both prediction and judgment?



What is the value of prediction in the absence of judgment?

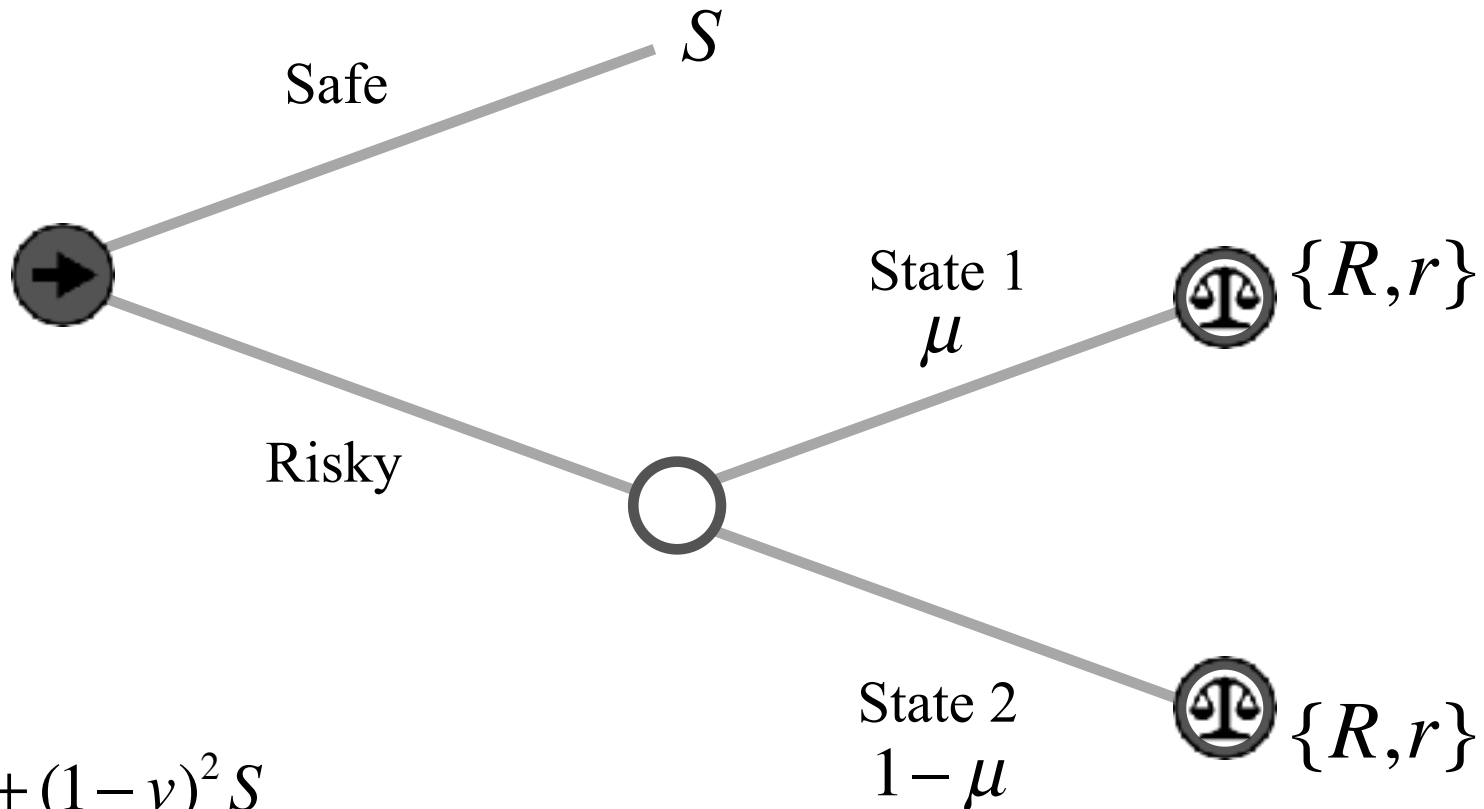
Allows state-contingent decision-making



$$\max\{vR + (1 - v)r, S\}$$

What is the value of judgment in the absence of prediction?

Allows identification of dominant actions



$$v^2 R + (1 - v)^2 S$$

$$+ v(1 - v) \max\{\mu R + (1 - \mu)r, S\}$$

$$+ (1 - v)v \max\{\mu r + (1 - \mu)R, S\}$$

Judgment as Thought

To work out the payoffs, you need to think (which takes time)

λ learn
 $1 - \lambda$ don't

λ learn
 $1 - \lambda$ don't



Apply judgment to state i
or
Just choose

Apply judgment to state j
or
Just choose

Choose

$$\frac{\lambda}{1 - (1 - \lambda)\delta} = \hat{\lambda}$$

Judgment options

*Suppose that (1) safe is a default and
(2) judgment alone is insufficient to switch
from default*

Learn neither	<i>Low $\hat{\lambda}$</i>	
Learn both states	<i>Dominated</i>	
Learn one state	<i>“Medium” $\hat{\lambda}$</i>	J1
Learn one state and other if ‘good’ news	<i>High $\hat{\lambda}$</i>	J2
Learn one state and other if ‘bad’ news	<i>Dominated</i>	

Learn neither

Learn one state

Learn one state and
other if ‘good’ news

$\hat{\lambda}_{J1}$

$\hat{\lambda}_{J2}$

Prediction Technology

With probability e , perfect forecast, otherwise none

$$\text{A1 (Safe Default)} \quad vR + (1 - v)r \leq S$$

$$\text{A2 (Judgment Insufficient)} \quad \mu R + (1 - \mu)r \leq S$$

$$\mu \geq \frac{1}{2}$$

Expected payoff:

$$\pi \equiv e \max\{\hat{\lambda}(vR + (1 - v)S), S\} + (1 - e) \max\{V_{J1}, V_{J2}, S\}$$

Complements or Substitutes?

$$\frac{\partial^2 \pi}{\partial e \partial \lambda} \geq 0 \text{ if } \hat{\lambda} < \hat{\lambda}_{J_2}$$

Complements

Substitutes

Learn neither

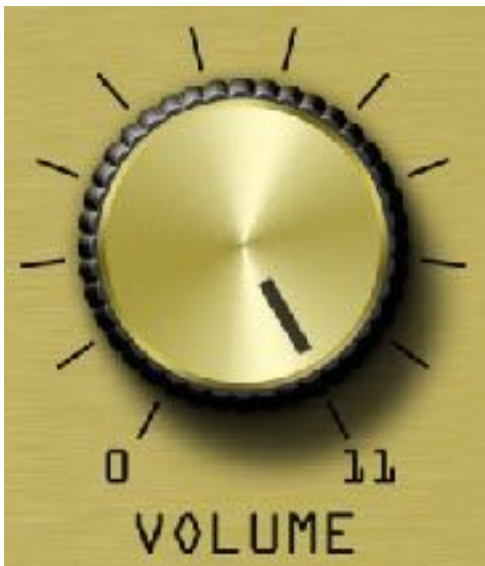
Learn one state

Learn one state and
other if 'good' news

$\hat{\lambda}_{J_1}$

$\hat{\lambda}_{J_2}$

Prediction



Rules



State-contingent
decisions

Complexity

$$\hat{\lambda} \underbrace{\sum_{i=1}^m \mu_i (vR + (1-v)S)}_{\text{Predicted by AI}} + \sum_{i=m+1}^N \mu_i S$$

As N increases (m fixed), value of prediction and judgment are reduced

Automation

“Any worker who now performs his task by following specific instructions can, in principle, be replaced by a machine. This means that the role of humans as the most important factor of production is bound to diminish—in the same way that the role of horses in agricultural production was first diminished and then eliminated by the introduction of tractors.” Wassily Leontief (1983)

$$\underbrace{\sum_{i=1}^k \mu_i (vR + (1-v)S)}_{\text{Automated}} + \underbrace{\hat{\lambda} \sum_{i=1}^m \mu_i (vR + (1-v)S)}_{\text{Human Judgment}} + \underbrace{\sum_{i=m+1}^N \mu_i S}_{\text{Automated}}$$

As N increases (m fixed), automation increases.

Contracting

$$\underbrace{\sum_{i=1}^k \mu_i (vR + (1-v)S)}_{\text{Contractible}} + \hat{\lambda} \underbrace{\sum_{i=1}^m \mu_i (vR + (1-v)S)}_{\text{Non-Contractible}} + \underbrace{\sum_{i=m+1}^N \mu_i S}_{\text{Contractible}}$$

Firm boundaries

$$\underbrace{\sum_{i=1}^k \mu_i (vR + (1-v)S)}_{\text{Outsourced}} + \hat{\lambda} \underbrace{\sum_{i=1}^m \mu_i (vR + (1-v)S)}_{\text{Integrated}} + \underbrace{\sum_{i=m+1}^N \mu_i S}_{\text{Outsourced}}$$

As m rises, the returns to integration rise.

As k increases, the returns to integration fall.

Bias, Noise and the Data Generating Process

- Elite vs non-elite college candidates: $p_E > p_N$
- Interviewers biased towards elites
- Non-elites are noisier (random variable of g)
- Hire “right” candidate if $rp_N + g > rp_E + b$
- $\text{Prob}\{g \text{ high enough}\} = \text{Prob}\{g > r(p_E - p_N) + b\} = q$

ML training:

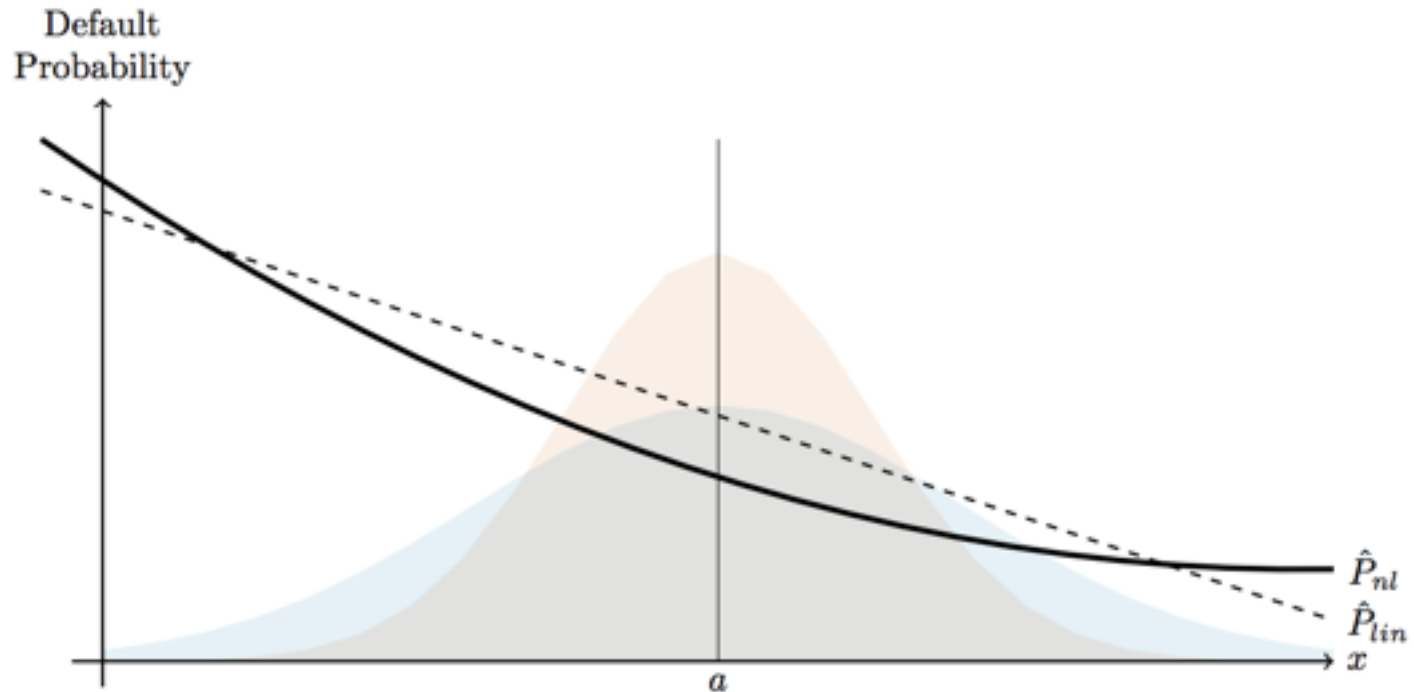
$$E[y | E] = (1 - q)p_E$$
$$E[y | N] = qp_N$$

Results:

- No noise ($q = 0$)
- No bias but noise: pick $\max\{(1-q)p_E, qp_N\}$
- High bias and high noise: will choose as if no bias
- ML will typically underestimate non-elites unless maximum noise $q = 1/2$.

Impact of Prediction on Markets

Figure 1: Unequal Effects of Better Technology



Conclusions

AI is about prediction and prediction only

Judgment is the process of determining rewards

Without prediction, judgment can identify
dominated actions

Judgment and prediction are complements unless
there is a high probability of finding dominated
actions

More complex tasks may not be less automated

As prediction improves, contractibility increases
but the effects on integration are ambiguous (more
for labour but less for capital)