

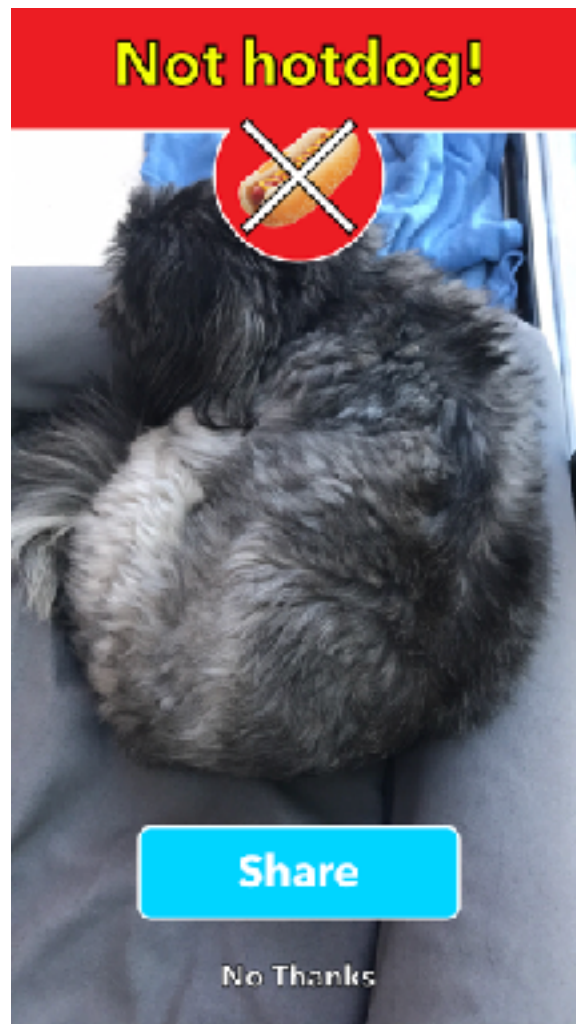
# Exploring the Impact of Artificial Intelligence: Prediction versus Judgment

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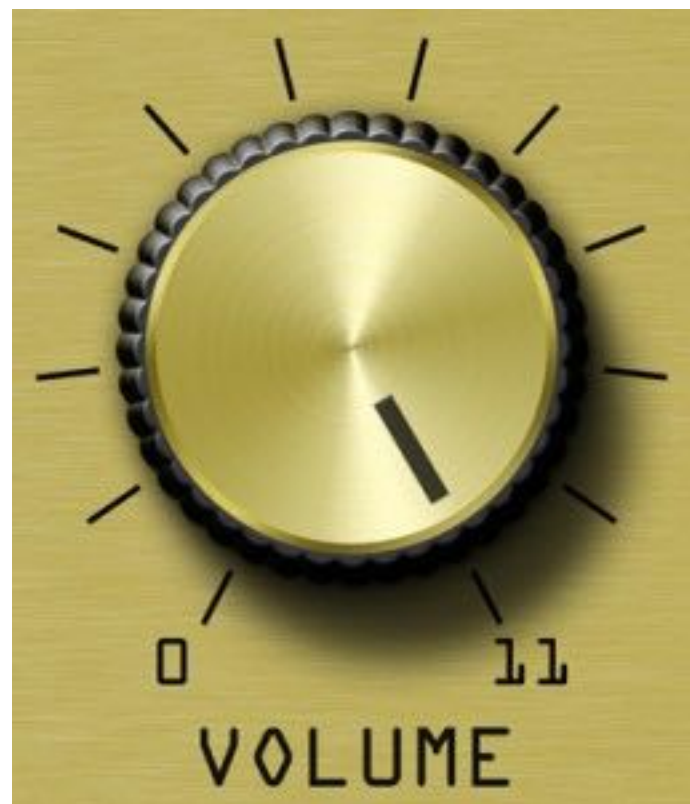
Recent AI is all about **prediction**





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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  
leaves an incredible trail of 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?

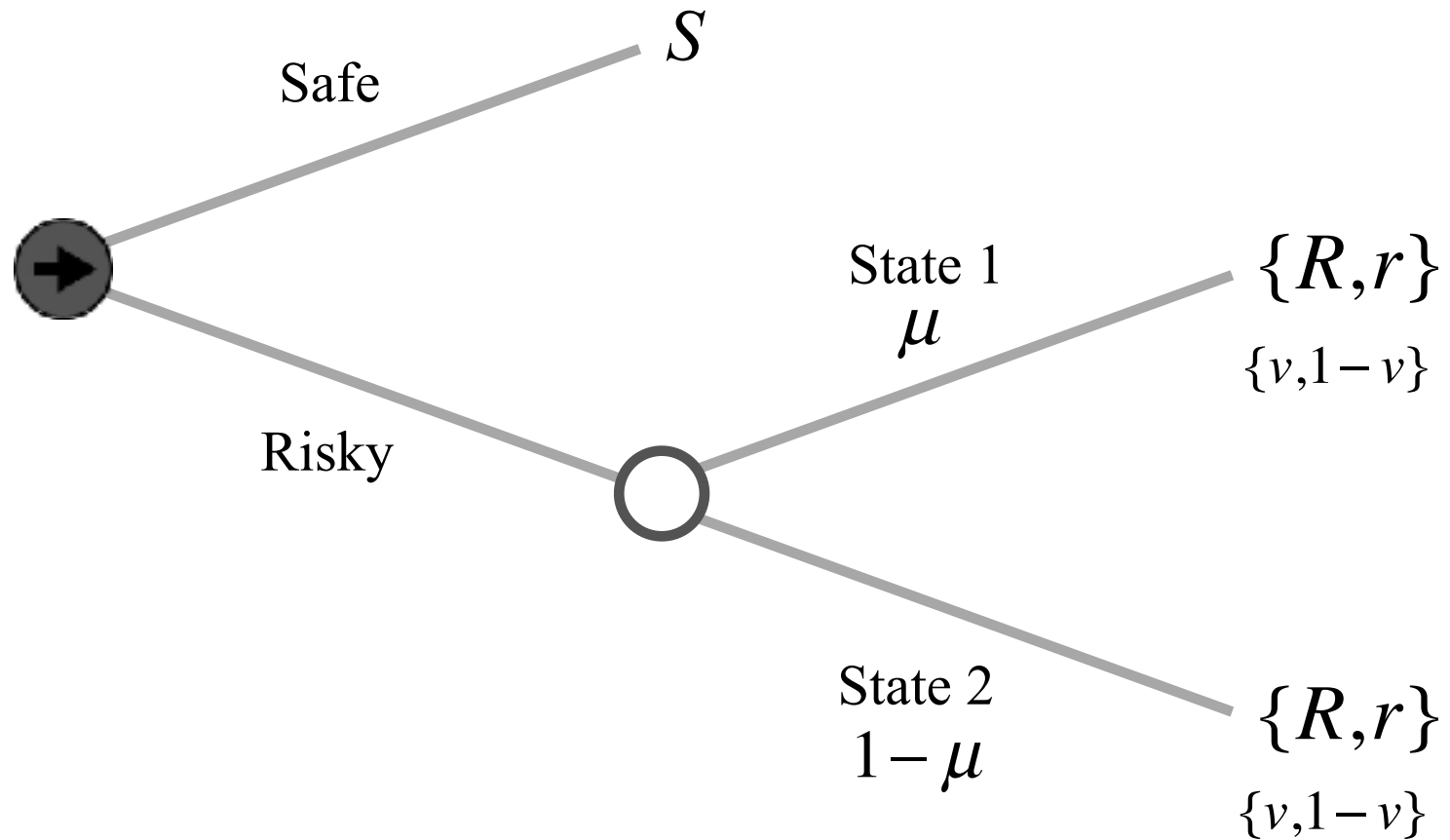
Thought

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?

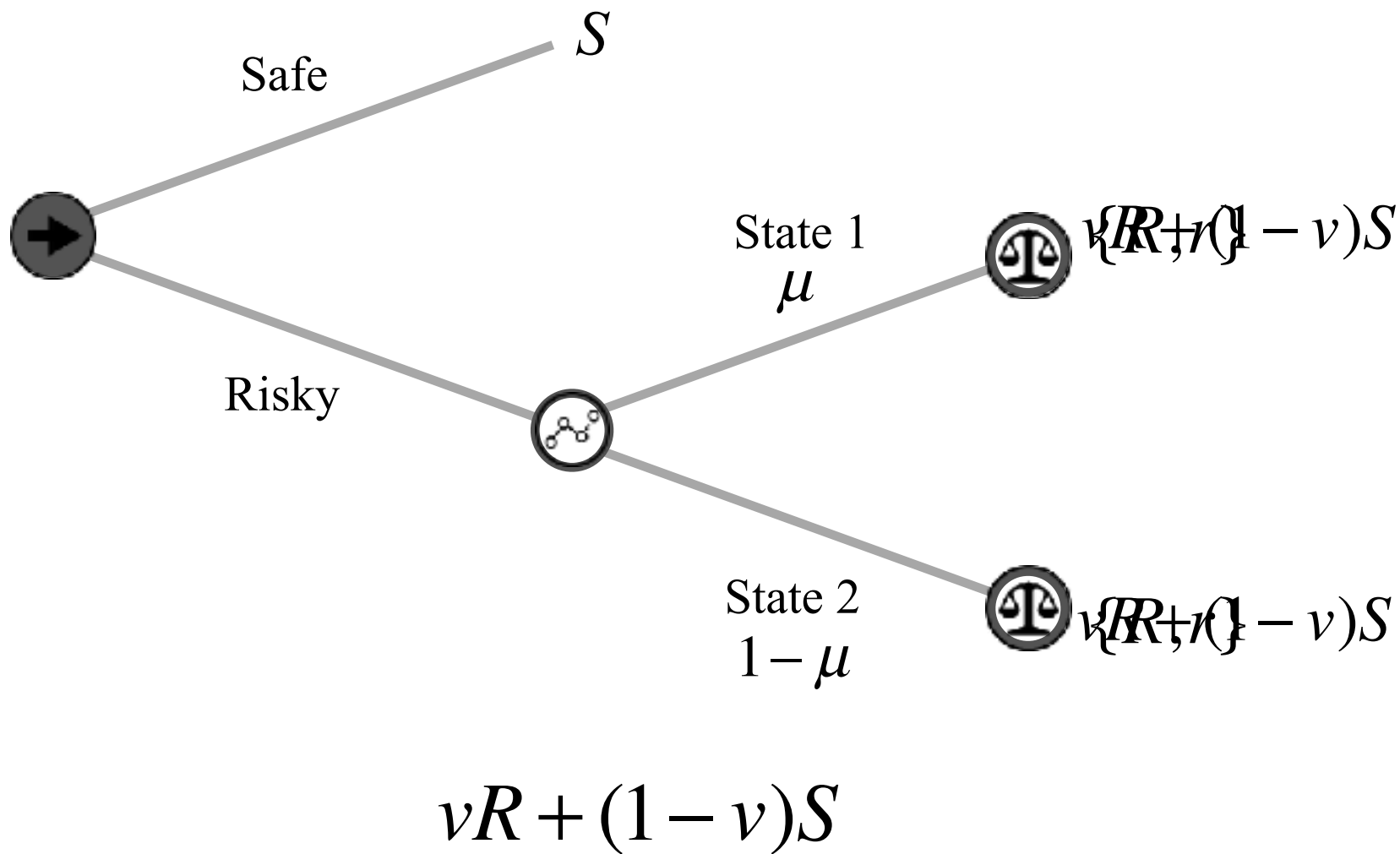
Simple intuition:

- 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)

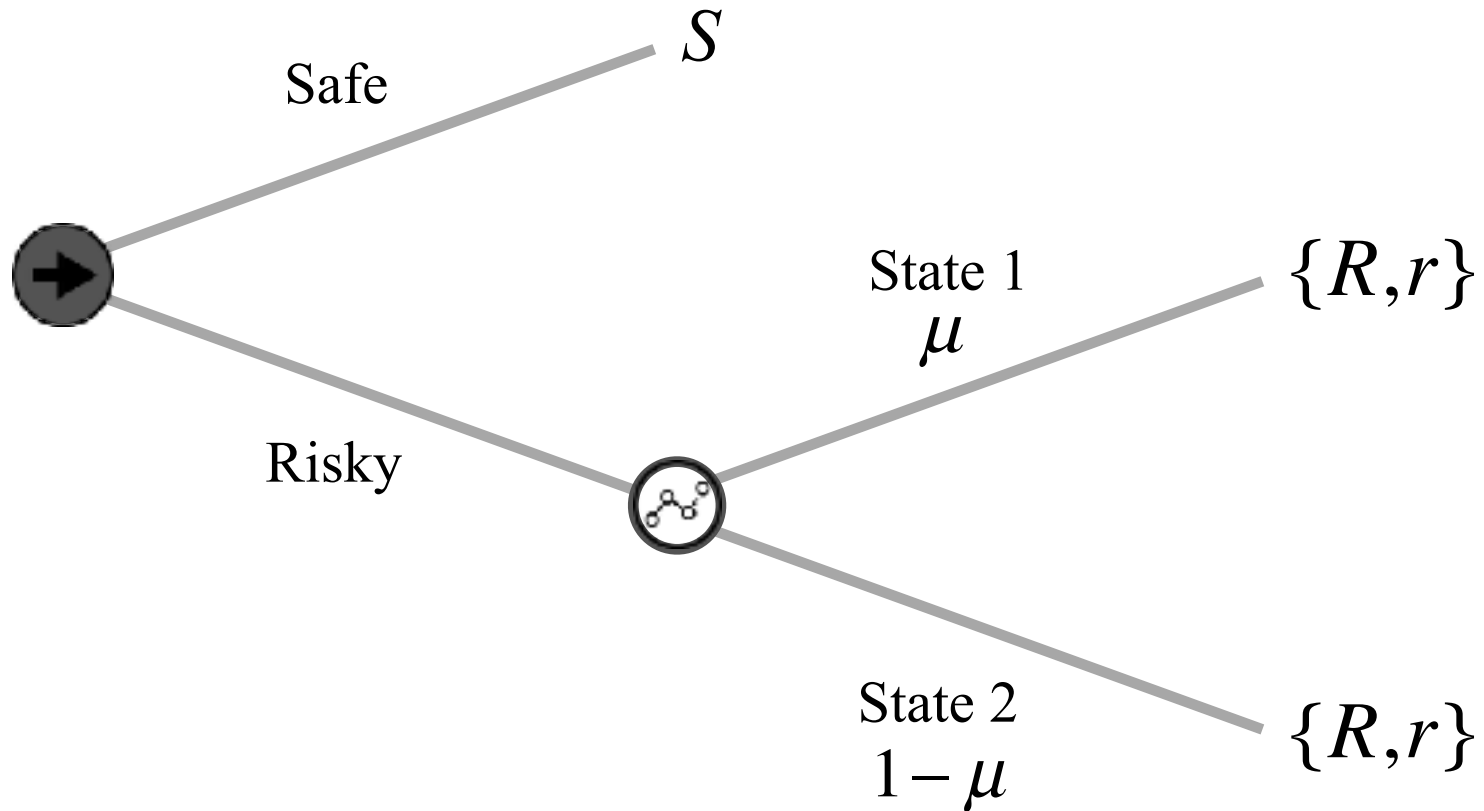


What happens if you have both prediction and judgment?



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

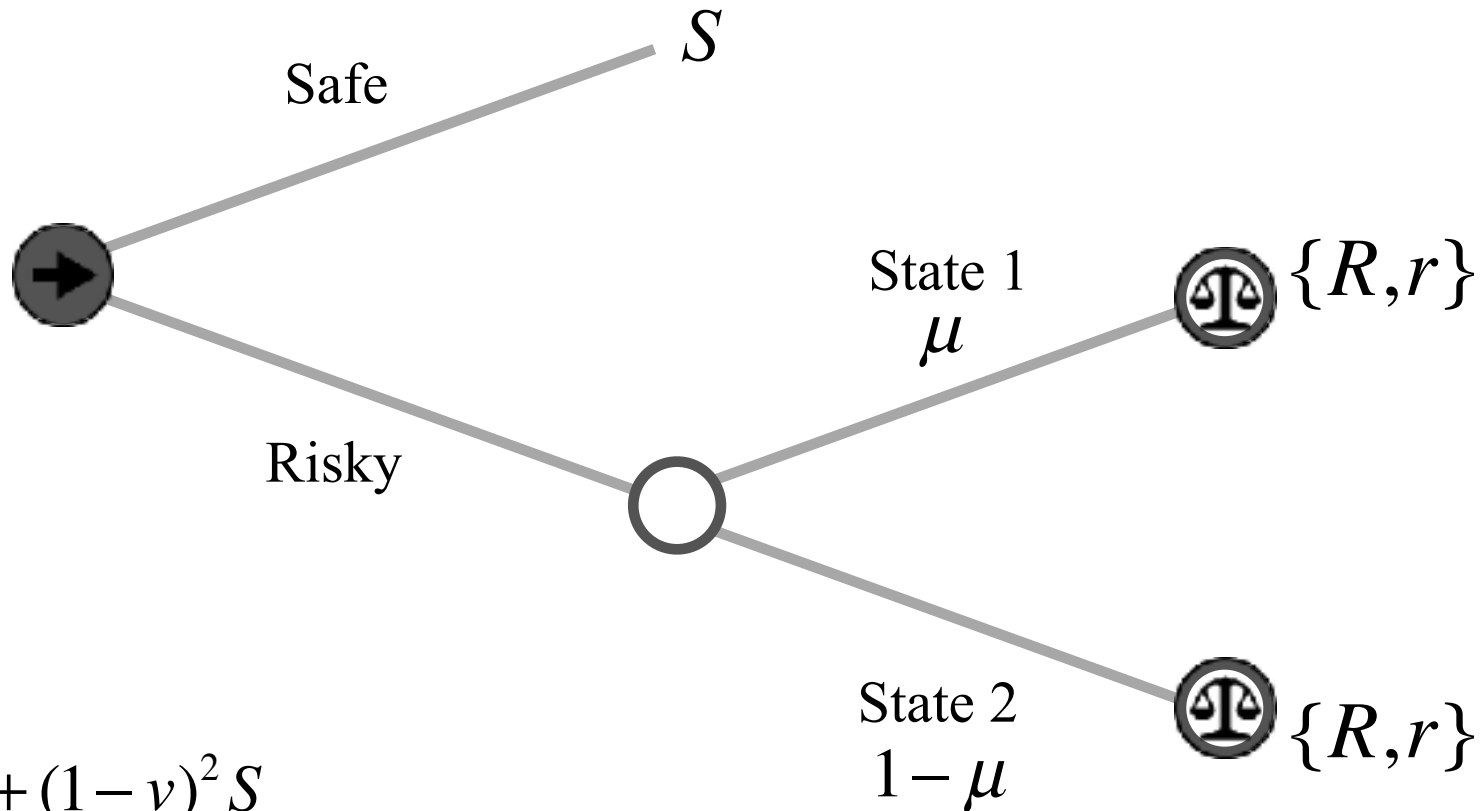
Allows state-contingent decision-making



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

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

Allows identification of dominant actions



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

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

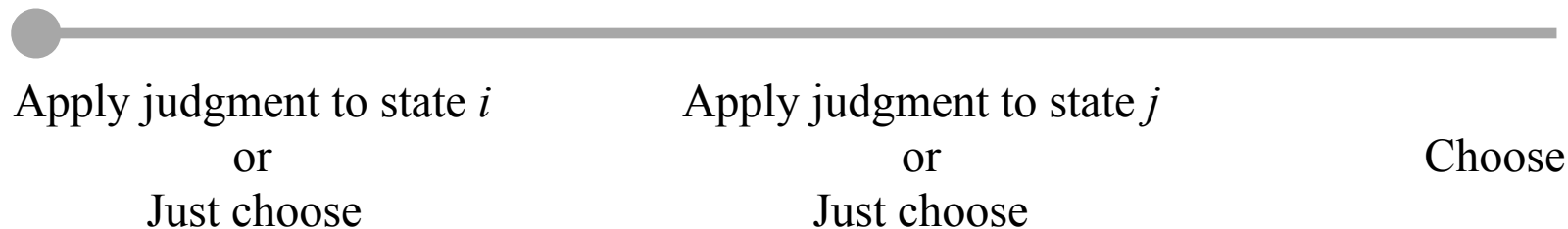
$$+ (1 - v)v \max\{\mu r + (1 - \mu)R, S\}$$

## Judgment as Thought

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

$\lambda$  learn  
 $1 - \lambda$  don't

$\lambda$  learn  
 $1 - \lambda$  don't



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

## Judgment options

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

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

Extensive margin:  $e$  is the probability the AI generates a prediction

Intensive margin:  $a$  is the probability the AI a generated prediction is correct

Trade-off: if design AI with higher  $e$ ,  $a$  is lower

**What happens to design as judgment becomes easier?**

$e$  falls and  $a$  is higher



## Complexity

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

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)*

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

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.

## 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)