Paper Review:
Using methods from machine learning to evaluate behavioral models of choice under risk and ambiguity

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Choice under Risk : Preliminaries

- Risk averse : People will prefer certainty over uncertainty.

  Example: people will prefer a choice with 2500 payoff without uncertainty over a choice with (expected) 2500 payoff with uncertainty.
- Expected Utility Model(EU): $\Sigma \mathrm{p_i u(x_i)}$
- Expected Utility with Probability Weighting Model(EUP):

$$\Sigma f(p_i)u(x_i), where\ f\ is\ the\ probability\ weighting\ function.$$

Note : f will overweight small probability and underweight large probability.

Choice under Risk : Preliminaries

- Regularized Regression: Regression Model (OLS) with penalty for model complexity.

Goal : Minimize $\left||y - X\beta|\right|_2 + \lambda\left||\beta|\right|_p$, where

$\left||\beta|\right|_p is\ be\ defined\ as(\Sigma|\beta_i\ \ |^p)\hat{}(1/p)$

Note: 1. λ can be seen as a shadow price for buying model complexity

2. In this paper, when p = 1, we call the model "Lasso" ;

when p = 2, we then call the model "Ridge".

3. When $\lambda = 0$, then we go back to OLS case.

Choice under Risk : Experimental Design

Participant will:

- Facing with choices about lotteries. In the lotteries, an urn containing 100 balls, some are red, some are blue and some are green, each with associated monetary prize.
- Give willingness to pay (WTP) to play lotteries.
- Facing 10 randomly generated lotteries.

In Experiments:

$\{p_{red},\ p_{blue},\ p_{green},\ money_{red}, money_{blue}\}$ will be generated randomly with $money_{green} = 0$.

Choice under Risk : Results

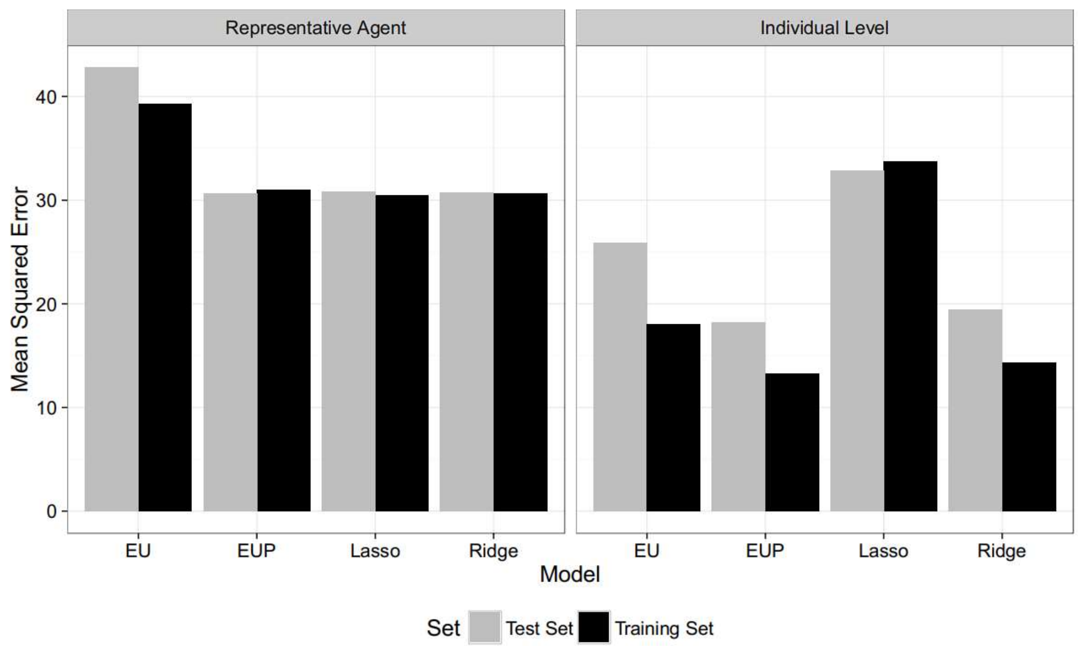

Fig. 2. ML methods outperform standard expected utility, but not expected utility with probability weighting. The representative agent assumption, where all individuals are assumed to have the same utility function, is highly restrictive.

Choice under Risk : Opening the Black Box

Two possi

- ML “re-
- ML lear ut yields the same

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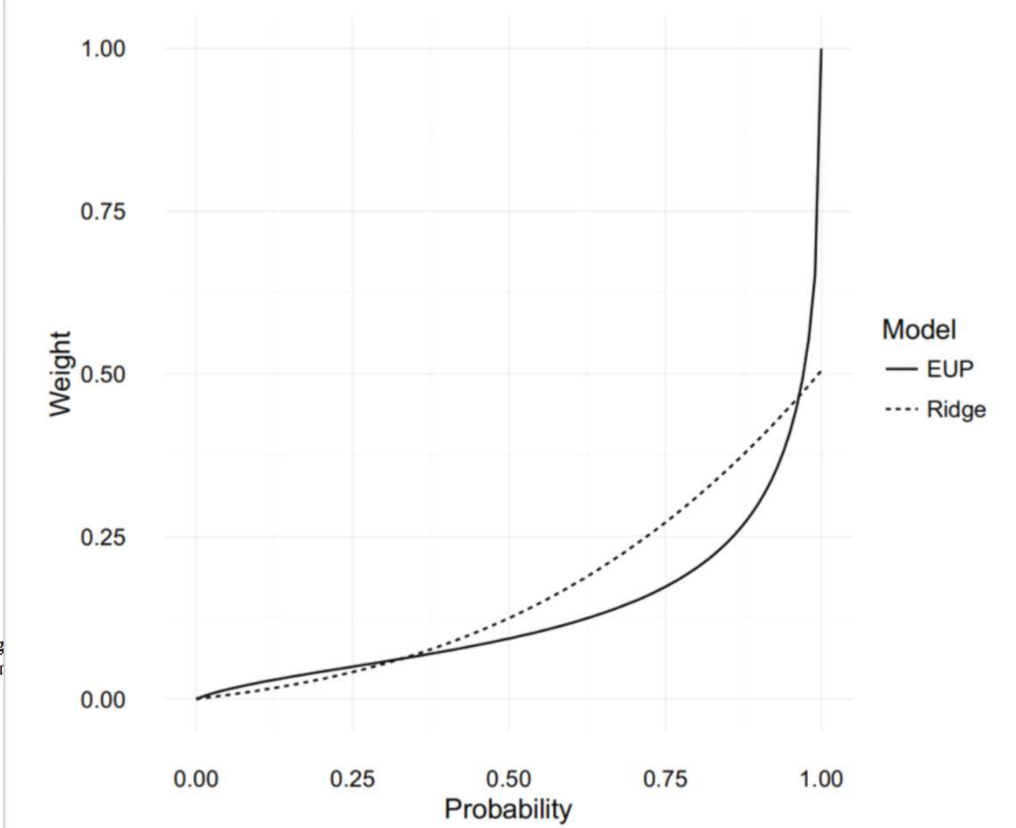

Fig. 4. Implied probability weighting curves for the EUP model (solid line) and the Ridge model.

Choice under Ambiguity : Preliminaries

- Ambiguity averse : People will prefer a (risky) choice with specific distribution over a (risky) choice with unknown distribution.

Example: People will prefer an urn with 50 red balls and 50 black balls over an urn with x red balls and 100-x black balls.

- Maximin models : $U(X,Y,z) = \big(I - \gamma(X+Y)\big)P(X,Y)z^{\alpha}$
- Second order expected utility(SOEU) :

$$U(X,Y,z) = \int (g(w)z^{\alpha})^{\gamma}\, dp(X,Y)$$

Choice under Ambiguity : Experimental Design

Participant will:

- Give WTP to play lotteries.
- Know at least X red balls and at least Y blue balls in the urn. However,

Table 2
Example of ambiguous lottery presentation in experiment.

	Red	Blue	Unknown
# Balls	At least 20	At least 31	49
Prize	$10	$0	??

In Experiments:

- $\{X_{red}, Y_{blue}, prize\}$ will be generated randomly.

Choice under Ambiguity : Results

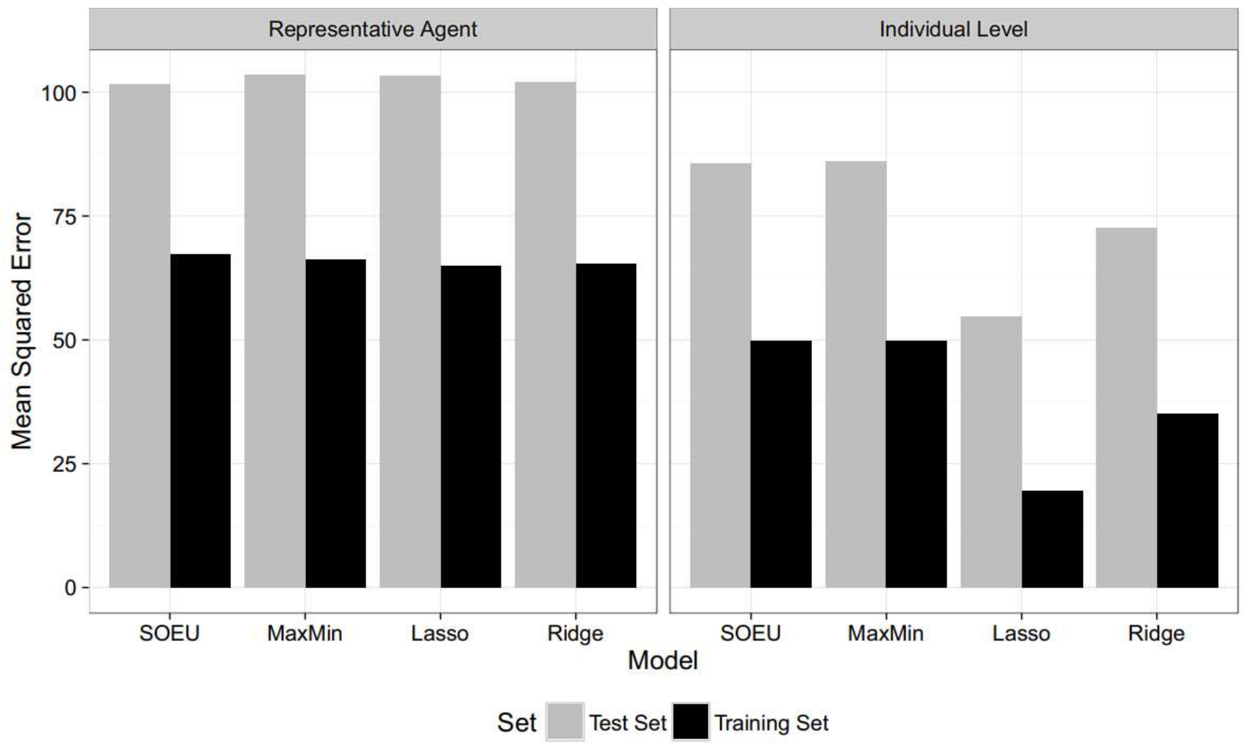

Fig. 5. ML methods outperform economic models in choice under ambiguity. This suggests that building a 'plug and play' ambiguity aversion model is a fruitful direction for both theorists and experimentalists alike.

Choice under Ambiguity : Opening the black box

- Ample roo
- Favorable i ily than unfavorabl ar 2015)

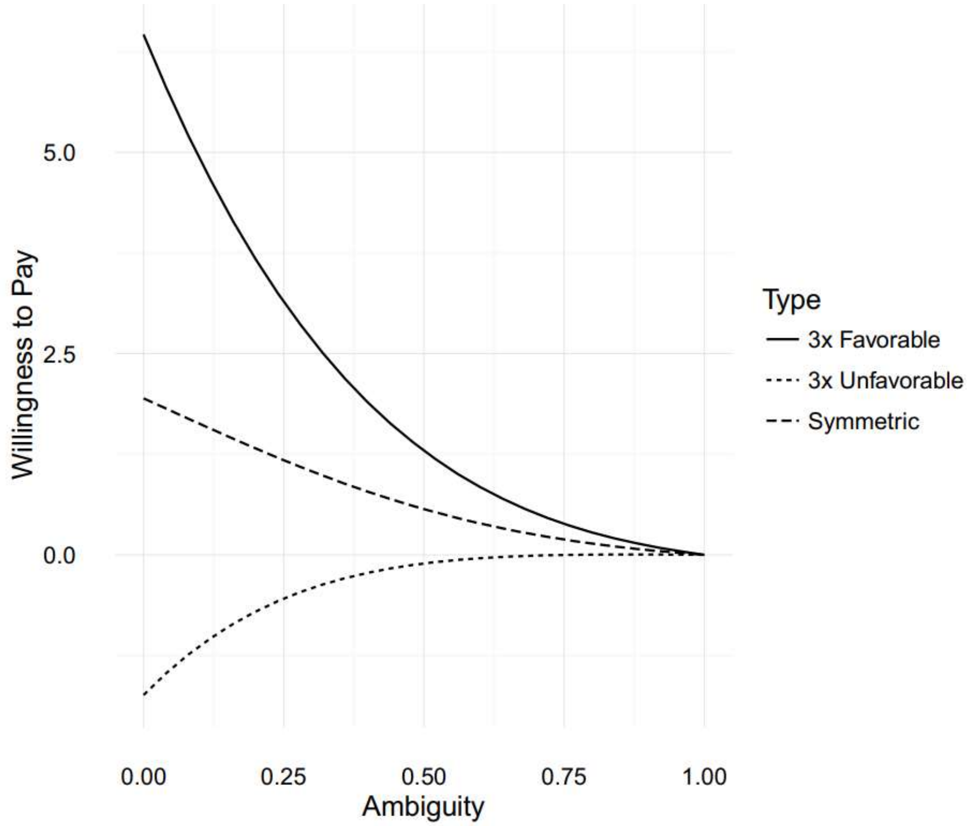

Fig. 6. Implied ambiguity penalty curves from predicted by the ridge model.

Paper Review:
What can the demand analyst learn from machine learning?

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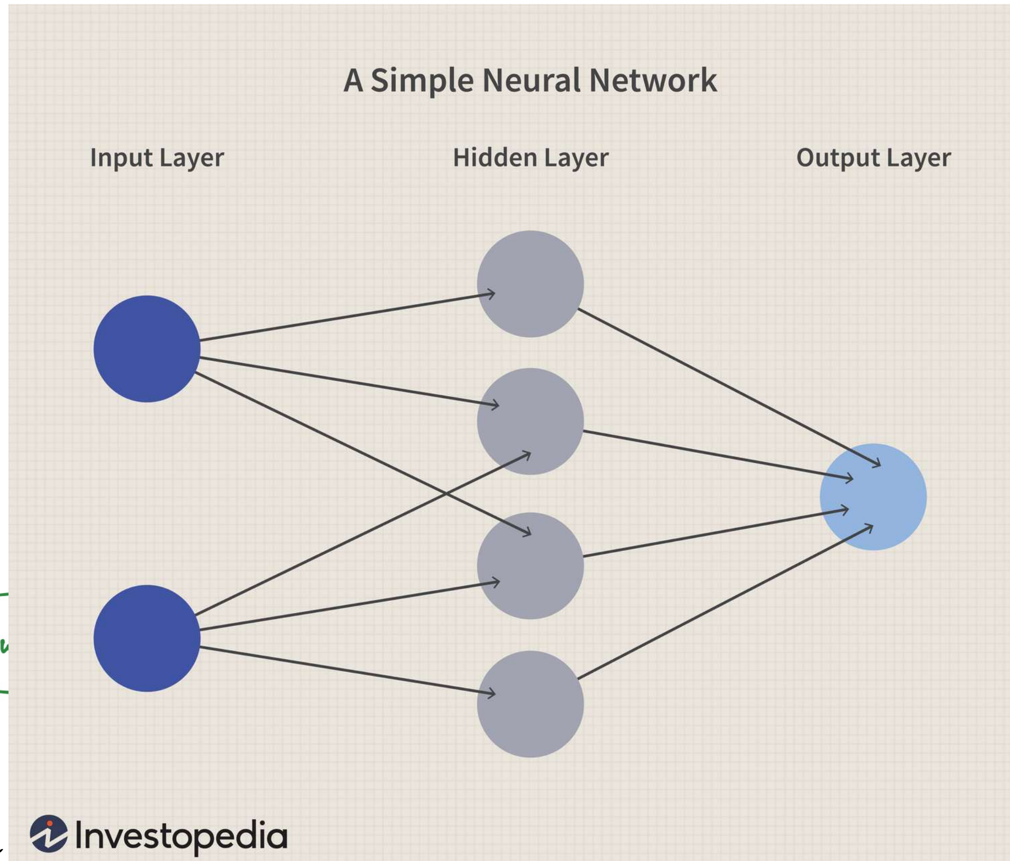
Preliminaries

- Rank I
  Give ... $\leq x_{[2]}$
  $\leq$ ... *t.*
- Compl
- Restric
- Arrow
- Decisi
- Neural ...



Sub Tree

High Risk

Lo

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Experimental Design

Participants will:

- Being given two equiprobable states denoted by $s = 1, 2$ and two associate arrow securities.
- Being given a budget line randomly.
- Being asked to allocate token between two arrow securities on the randomly selected budget line.
- Facing 50 independent decision problems.

Results

Table 1: The completeness and restrictiveness of RDU and ML models

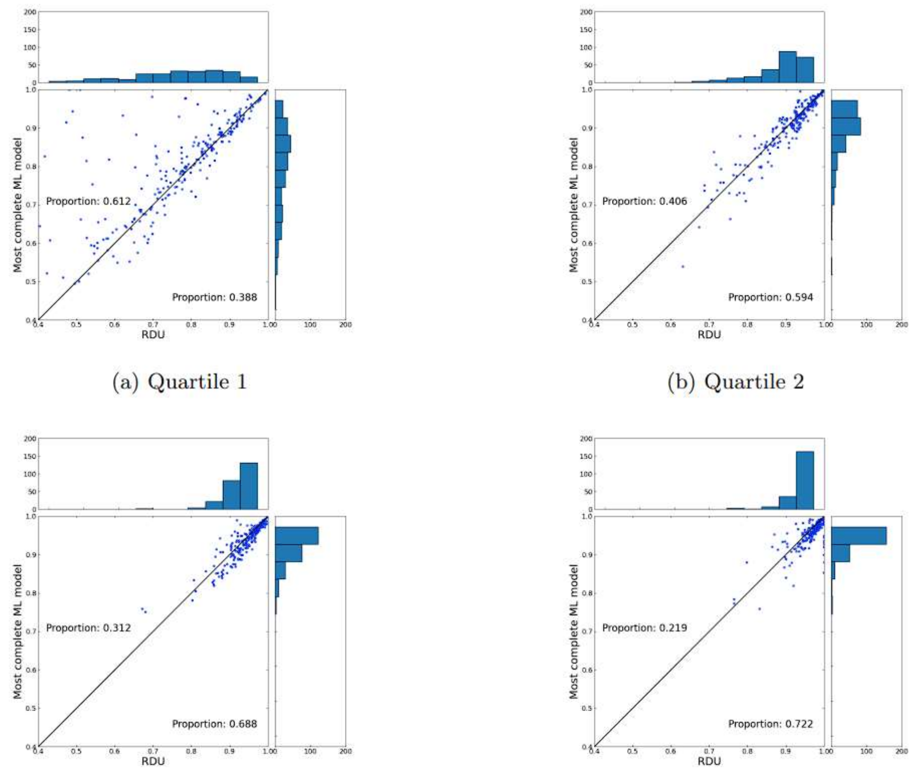
	Average	RDU's win rate	RDU's win rate against ML by rationality quartiles				Absolute completeness difference between RDU and ML by rationality quartiles				
Panel A: RDU and ML model classes	completeness	against ML	1st	2nd	3rd	4th	1st	2nd	3rd	4th	Restrictiveness
RDU	89.8% [89.1%, 90.5%]	-	-	-	-	-	-	-	-	-	23.4%
Regularized Regressions	82.6% [81.7%, 83.5%]	82.6%	55.4%	84.9%	93.8%	96.6%	0.9%	5.6%	7.5%	14.8%	27.4%
Tree-based Models	89.5% [88.8%, 90.2%]	68.6%	60.8%	67.4%	71.7%	74.7%	1.4%	0.7%	0.8%	1.0%	14.8%
Neural networks	79.7% [78.4%, 80.8%]	91.2%	79.6%	90.0%	95.8%	99.6%	5.7%	9.0%	9.2%	16.8%	20.4%
Panel B: Regularized regressions											
LASSO	78.0% [76.9%, 79.0%]	88.6%	71.3%	91.2%	93.8%	98.3%	5.0%	9.2%	11.8%	21.6%	29.3%
LASSO+	78.3% [77.2%, 79.3%]	87.3%	65.8%	91.2%	94.2%	98.3%	3.4%	9.1%	11.9%	21.7%	27.1%
Ridge	82.1% [81.2%, 82.9%]	88.0%	67.9%	88.3%	96.3%	99.6%	1.6%	6.1%	8.1%	15.2%	27.1%
Panel C: Tree-based models											
Mean	86.9% [86.1%, 87.7%]	84.4%	77.1%	88.3%	85.8%	86.5%	2.7%	3.7%	2.7%	2.5%	17.4%
Linear	83.6% [82.5%, 84.6%]	86.5%	80.8%	85.8%	87.1%	92.4%	10.1%	5.7%	4.4%	4.5%	7.6%
SVR	86.0% [85.2%, 86.8%]	88.5%	80.0%	90.4%	87.5%	96.2%	3.6%	3.9%	3.3%	4.4%	15.1%
RF	88.4% [87.7%, 89.1%]	79.8%	69.6%	78.7%	80.4%	90.7%	0.3%	1.6%	1.6%	2.1%	16.8%

Results

Table 2: The completeness and restrictiveness of EUT and RDU

Panel A: EUT and RDU	Average completeness	EUT win rate against RDU	EUT's win rate against RDU by rationality quartiles: 1st	2nd	3rd	4th	Absolute completeness difference between EUT and RDU by rationality quartiles: 1st	2nd	3rd	4th	Restrictiveness
EUT	89.8% [89.1%, 90.5%]	-	-	-	-	-	-	-	-	-	26.2%
RDU	89.8% [89.1%, 90.5%]	57.0%	67.5%	66.1%	51.3%	43.0%	0.5%	0.2%	-0.4%	-0.3%	23.4%
Panel B: CRRA Only											
EUT CRRA	89.4% [88.7%, 90.1%]	-	-	-	-	-	-	-	-	-	25.3%
RDU CRRA	89.4% [88.7%, 90.1%]	51.4%	65.4%	59.0%	43.3%	37.6%	0.6%	0.2%	-0.5%	-0.3%	23.1%
Panel C: CARA Only											
EUT CARA	89.1% [88.3%, 89.8%]	-	-	-	-	-	-	-	-	-	27.4%
RDU CARA	89.1% [88.3%, 89.8%]	56.1%	64.6%	64.9%	55.0%	39.7%	0.4%	0.1%	-0.3%	-0.2%	23.9%

Results



(a) Quartile 1

(b) Quartile 2

(c) Quartile 3

(d) Quartile 4

Figure 2: Scatterplot of completeness of RDU and the most complete machine learning model by rationality quartile.