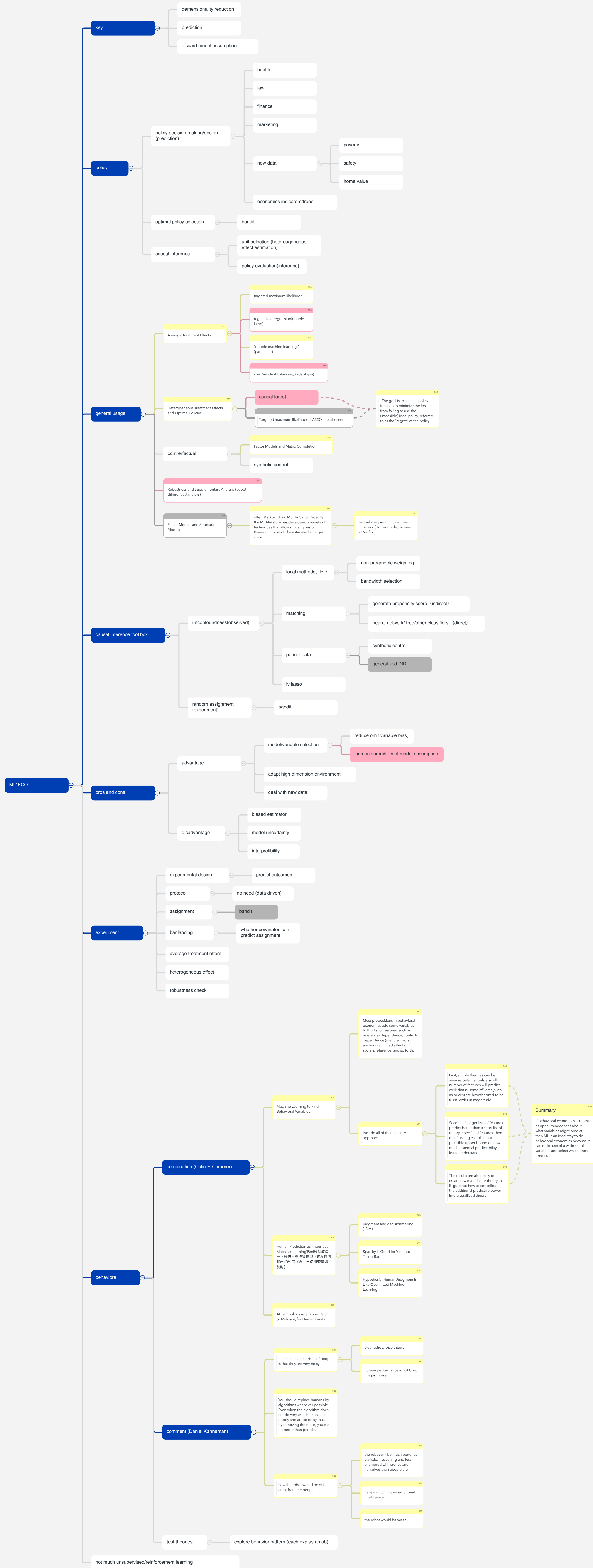
ML*ECO
key
demensionality reduction
prediction
discard model assumption
policy
policy decision making/design (prediction)
health
law
finance
marketing
new data
poverty
safety
home value
economics indicators/trend
optimal policy selection
bandit
causal inference
unit selection (heterougeneous effect estimation)
policy evaluation(inference)
general usage
Average Treatment Effects
targeted maximum likelihood
regularized regression(double lasso)
“double machine learning,” (partial out)
ipw, “residual balancing,”(adapt ipw)
Heterogeneous Treatment Effects and Optimal Policies
causal forest
Targeted maximum likelihood, LASSO, metalearner
. The goal is to select a policy function to minimize the loss from failing to use the (infeasible) ideal policy, referred to as the “regret” of the policy.
contrerfactual
Factor Models and Matrix Completion
synthetic control
Robustness and Supplementary Analysis (adopt different estimators)
Factor Models and Structural Models
often Markov Chain Monte Carlo. Recently, the ML literature has developed a variety of techniques that allow similar types of Bayesian models to be estimated at larger scale.
textual analysis and consumer choices of, for example, movies at Netflix.
causal inference tool box
unconfoundness(observed)
local methods，RD
non-parametric weighting
bandwidth selection
matching
generate propensity score（indirect）
neural network/ tree/other classifiers （direct）
pannel data
synthetic control
generalized DID
iv lasso
random assignment (experiment)
bandit
pros and cons
advantage
model/variable selection
reduce omit variable bias,
increase credibility of model assumption
adapt high-dimension environment
deal with new data
disadvantage
biased estimator
model uncertainty
interpretibility
experiment
experimental design
predict outcomes
protocol
no need (data driven)
assignment
bandit
banlancing
whether covariates can predict assignment
average treatment effect
heterogeneous effect
robustness check
behavioral
combination (Colin F. Camerer)
Machine Learning to Find Behavioral Variables
Most propositions in behavioral economics add some variables to this list of features, such as reference- dependence, context- dependence (menu eff ects), anchoring, limited attention, social preference, and so forth.
include all of them in an ML approach
First, simple theories can be seen as bets that only a small number of features will predict well; that is, some eff ects (such as prices) are hypothesized to be fi rst- order in magnitude
Second, if longer lists of features predict better than a short list of theory- specifi ed features, then that fi nding establishes a plausible upper bound on how much potential predictability is left to understand
The results are also likely to create raw material for theory to fi gure out how to consolidate the additional predictive power into crystallized theory
Summary
If behavioral economics is recast as open- mindedness about what variables might predict, then ML is an ideal way to do behavioral economics because it can make use of a wide set of variables and select which ones predict.
Human Prediction as Imperfect Machine Learning把ml模型改造一下模仿人类决策模型（过度自信和ml的过度拟合，当使用变量增加时）
judgment and decisionmaking (JDM).
Sparsity Is Good for Y ou but Tastes Bad
Hypothesis: Human Judgment Is Like Overfi tted Machine Learning
AI Technology as a Bionic Patch, or Malware, for Human Limits
comment (Daniel Kahneman)
the main characteristic of people is that they are very noisy
stochastic choice theory
human performance is not bias, it is just noise
You should replace humans by algorithms whenever possible. Even when the algorithm does not do very well, humans do so poorly and are so noisy that, just by removing the noise, you can do better than people.
how the robot would be diff erent from the people
the robot will be much better at statistical reasoning and less enamored with stories and narratives than people are
have a much higher emotional intelligence
the robot would be wiser
test theories
explore behavior pattern (each exp as an ob)
not much unsupervised/reinforcement learning