

Introduction to CausalML

Aug 2021

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Uber



CausalML

^[1] Uber Technologies ^[2] Toyota Research Institute

Agenda

01 Why CausalML?

- Motivation and Use cases
- Highlights and Functionality overview

02 Get started with CausalML

03 Main modules

- Meta-learners and Uplift trees models
- Value optimization models
- Interpretation & Visualisation
- Data Generation and PSM

04 Summary

KDD website: https://t.uber.com/kdd_causalm1

(or <https://causal-machine-learning.github.io/kdd2021-tutorial>)

Installation: <https://github.com/uber/causalm1#installation>

Notebook: <https://github.com/uber/causalm1/tree/master/examples>

Why CausalML

Why CausalML | Motivation

Forecast based on data

Questions:

- How many orders do we expect to receive next week?
- What's the predicted conversion rate for each user?

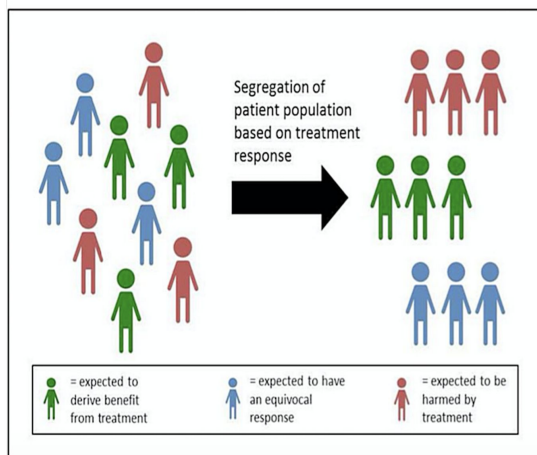
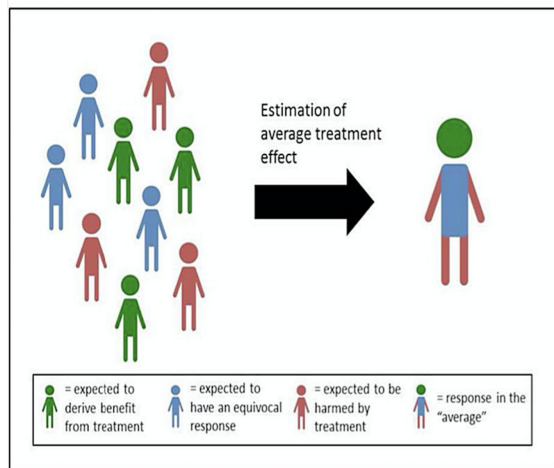
Actionable insight based on data

Questions:

- **What can we do** to increase the # of orders?
- What would have been the # of orders **if we had rolled out** Olympics advertisement **more broadly**?
- Will we still be able to obtain a similar increase in Conversion rate **if we only send out promo code to certain subpopulations**?

→ Require **Causal** understanding of data **rather than just Correlation**
→ Require estimation on **Conditional Average Treatment Effect**

Why CausalML | Motivation



Direction for solution

- From ATE to CATE
- “Actionable” insights

Enables personalized experience & Optimize for incremental effects

Causal Inference + Machine Learning

Develop optimization applications based on the unlocked insights

- Require **Causal** understanding of data rather than just **Correlation**
- Require estimation on **Conditional Average Treatment Effect**

Why CausalML | Real-World Applications

Personalization

We can engage with users more effectively by learning heterogeneous treatment effect, for example, provide meaningful and proactive customer support

Observational Causal Inference on User actions

In User Action and Customer Value Analysis project, we measure the impact of cross-sell conversions to existing users' long-term value.

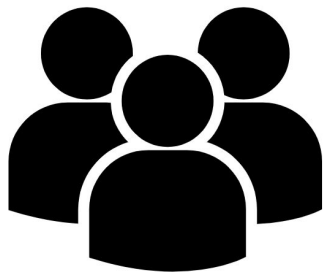
[Case Study #1: CeViChE](#)

Budget Optimization

Ads Targeting: we can use uplift modeling to optimize return on ads spend by selecting persuadable user group. [Case Study #2: Bidder](#)

Promo Targeting: we use causal inference estimation to spend budget on users who is estimated to have better treatment effect

Why CausalML | One-stop shop of Machine Learning for Causal Inference



Dedicated support

It's incubated for **long-term support** from Uber and community developers, we continue working actively with users to maintain and develop new functions and models.



Ease of Use

We follow **standardized machine learning library interface**. It's super easy to onboard and develop your use case with few lines of code. Also, **extensibility for growth is our package design principle**.



Industrial Use Cases

We aim to tackle **real-world large scale data and industrial applications** and continue to improve the efficiency of model implementation. We welcome collaborations on package development & use cases!



Rich Features

CausalML provides functions ranging from data generating, to PSM, to tree-based and meta-learners models. We **democratise uplift modeling methods** in academic paper and continue to add innovative in-house algorithms!

Summary | Core team and Contributors

Shoutout to all the contributors¹ of CausalML community!

Dahee Lee
Huigang Chen
Jeong-Yoon Lee
Jing Pan
Mike Yung
Mert Bay
Paul Lo
Totte Harinen
Yifeng Wu
Zhenyu Zhao

Yuchen (@yluogit)
Manoj (@manojbalaji1)
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Harsh (@HarshCasper)
Fritz (@fritzo)
Tomasz (@TomaszZamacinski)
Georg (@waltherg)
Florian (@FlorianWilhelm)
Harry (@deeplaunch)
Katherine (@khof312)

Steve (@steveyang90)
Vaclavbelak (@vaclavbelak)
Mario (@mwijaya3)
Christophe (@ccrndn)
Jannik (@jroessler)
Matthew (@maccam912)
Leo (@lleiou)
Mohamed (@ibraaaa)

downloads 401k

☆ Star 2,165

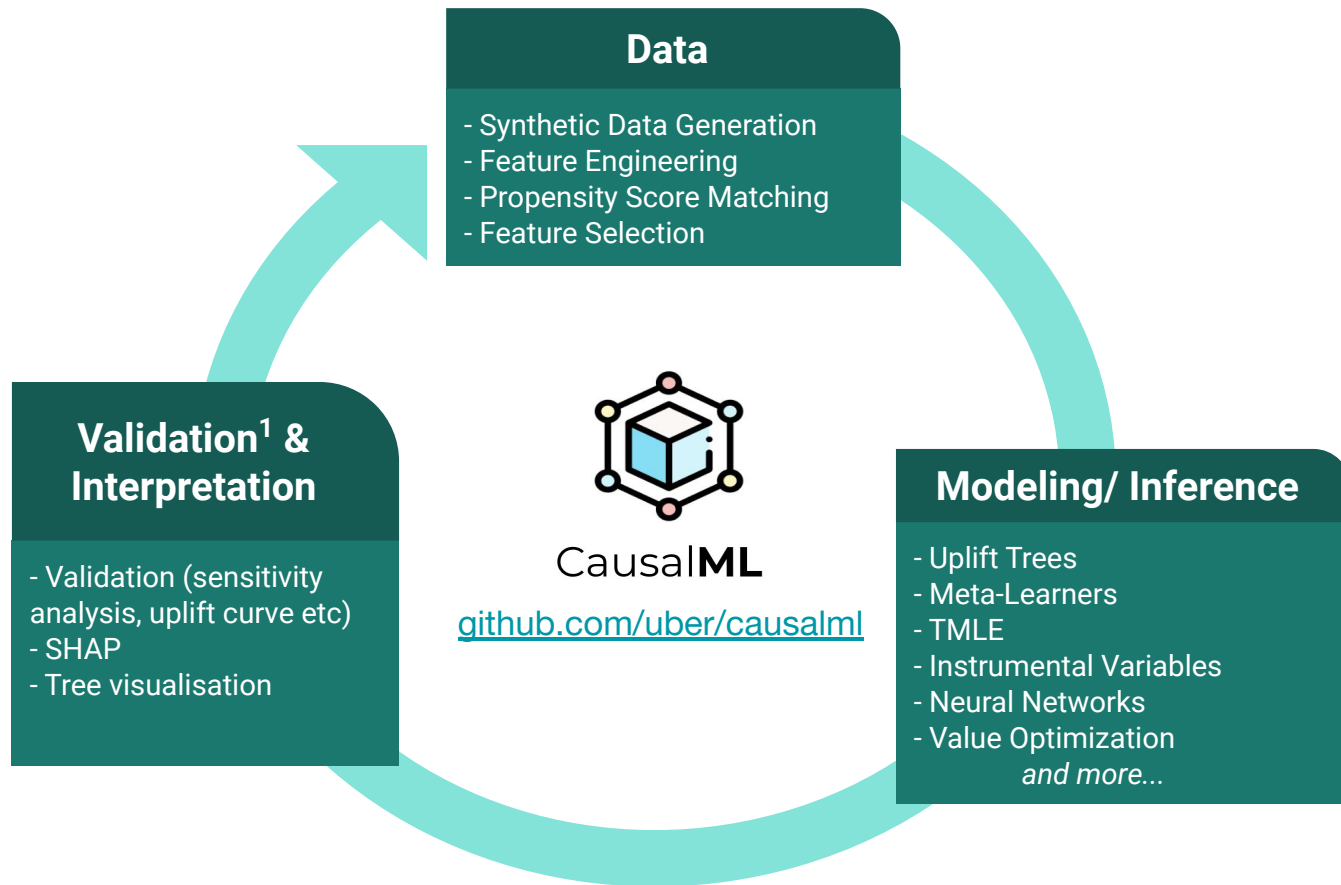
Contributors 26



+ 15 contributors

¹ List of contributors: <https://github.com/uber/causalml/graphs/contributors>

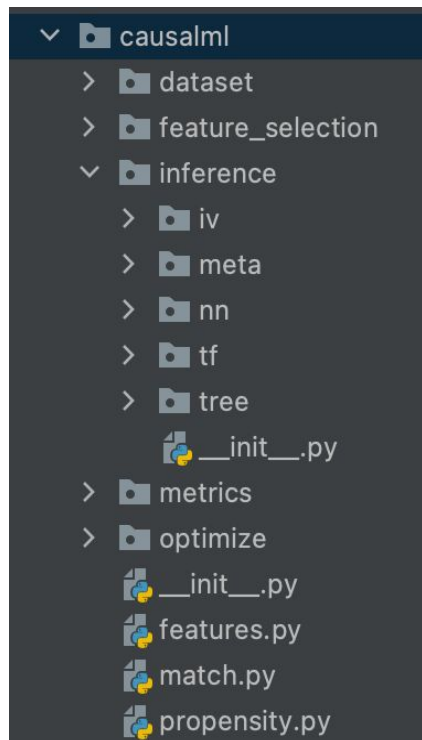
Why CausalML | Overview



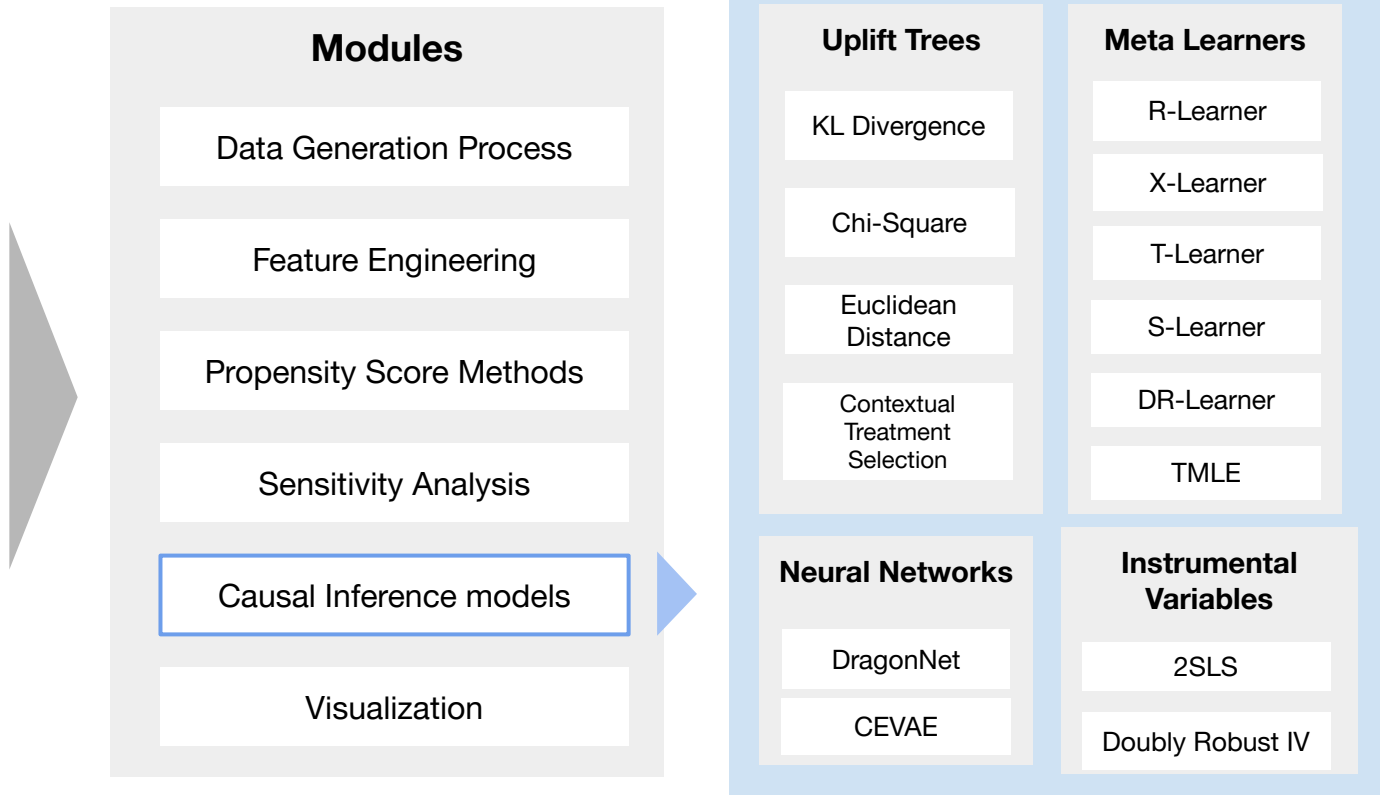
¹ Validation in Causal Inference: <https://causalml.readthedocs.io/en/latest/validation.html>

Why CausalML | Overview

Package structure



Modules and Key Algorithms



Get Started with CausalML

Get started | Package installation (v0.11)

Local with Conda

Recommend to use conda

```
$ git clone https://github.com/uber/causalml.git
$ cd causalml/envs/
$ conda env create -f environment-py38.yml
$ conda activate causalml-py38
```

For tensorflow (required for [DragonNet](#)^[1] model)

```
$ git clone https://github.com/uber/causalml.git
$ cd causalml/envs/
$ conda env create -f environment-tf-py38.yml
$ conda activate causalml-tf-py38
(causalml-tf-py38) pip install -U numpy
```

Google Colab (or other cloud instance)

```
!pip install causalml
```

```
[1] !pip install causalml

Collecting causalml
  Downloading causalml-0.11.1.tar.gz (243 kB)
    |#####| 243 kB 6.8
Requirement already satisfied: setuptools>=41.0.0 in /usr/local/lib/python3.8/dist-packages (from causalml)
Requirement already satisfied: pip>=10.0 in /usr/local/lib/python3.8/dist-packages (from causalml)
Requirement already satisfied: numpy>=1.18.5 in /usr/local/lib/python3.8/dist-packages (from causalml)
Requirement already satisfied: scipy>=1.4.1 in /usr/local/lib/python3.8/dist-packages (from causalml)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.8/dist-packages (from causalml)
```

```
[2] import causalml
    print(causalml.__version__)

0.11.1
```

For tensorflow

```
!pip install causalml[tf]
```

- Support python 3.6, 3.7, 3.8, 3.9
- Package installation
<https://github.com/uber/causalml#installation>
- Notebook example
<https://github.com/uber/causalml/tree/master/examples>

^[1] Shi, Claudia, David M. Blei, and Victor Veitch. "Adapting neural networks for the estimation of treatment effects." 33rd Conference on Neural Information Processing Systems (NeurIPS 2019), 2019.

Main Modules

Meta-learners and Uplift Trees

Value Optimization

Visualization

Data Generation and PSM

CausalML | Overview

Modules

Data Generation Process

Feature Engineering

Propensity Score Methods

Sensitivity Analysis

Causal Inference models

Visualization

Uplift Trees

KL Divergence

Chi-Square

Euclidean
Distance

Contextual
Treatment
Selection

Meta Learners

R-Learner

X-Learner

T-Learner

S-Learner

DR-Learner

TMLE

Neural Networks

DragonNet

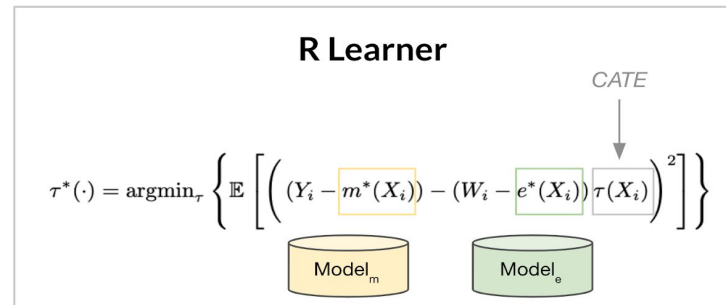
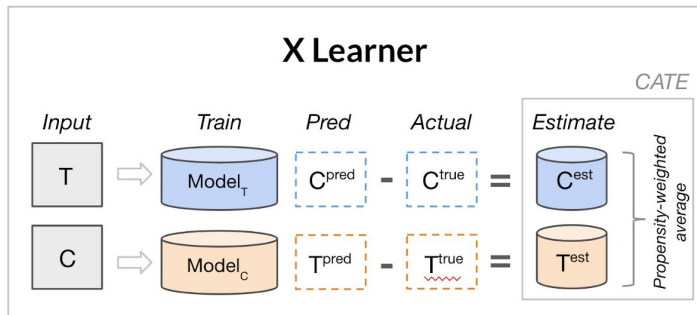
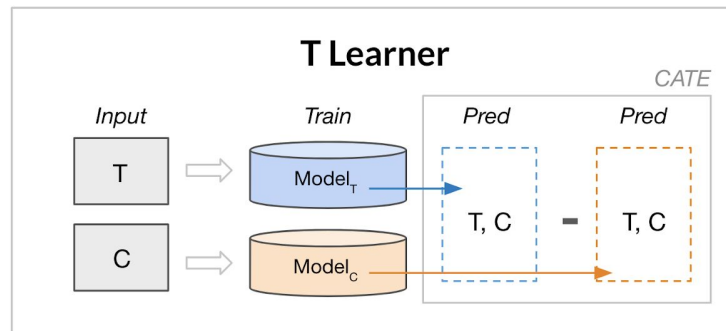
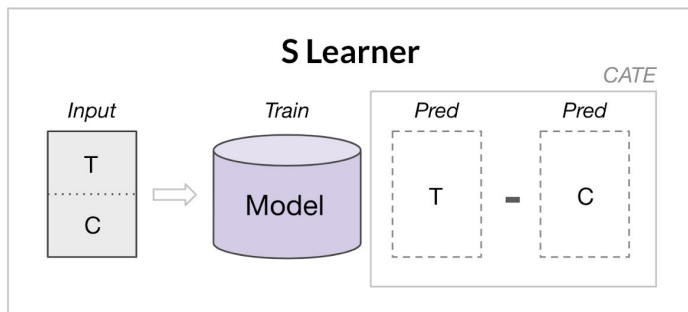
CEVAE

Instrumental Variables

2SLS

Doubly Robust IV

CausalML | Meta-learners: methodology



CausalML | Overview

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CausalML | Uplift Trees: methodology

Classification Tree

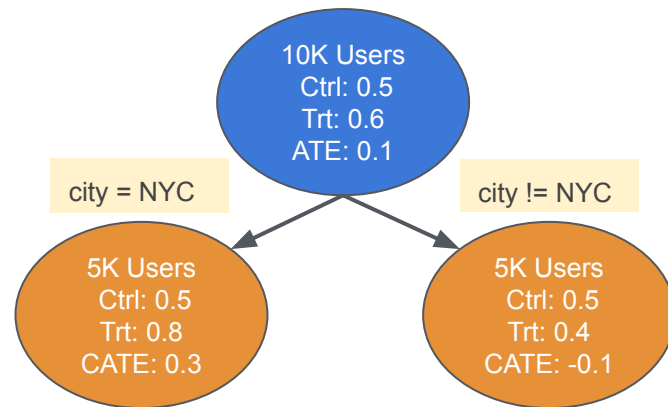
Goal: Predicting the conversion rate for the user

Loss function for tree split: The divergence with respect to the conversion rate. A split is great if the left node and right node has quite different conversion rate.

Uplift Tree

Goal: Predicting the treatment effect for the user

Loss function for tree split: The divergence with respect to the treatment effect. A split is great if the left node and the right node has quite different treatment effect.



Example loss: KL divergence

$$D_{KL}(P_t||P_c) = P_t(Y=1)\log\left(\frac{P_t(Y=1)}{P_c(Y=1)}\right) + P_t(Y=0)\log\left(\frac{P_t(Y=0)}{P_c(Y=0)}\right)$$

CausalML | CATE estimation example

Conditional Average Treatment Effect (CATE)

```
from causalml.inference.meta import BaseSRegressor
from xgboost import XGBRegressor

y, X, treatment, _, _, e = synthetic_data(mode=1, n=N_SAMPLES, p=N_FEATURES)
X_multi = np.array(['treatment_A' if x == 1 else 'control' for x in treatment])

learner_s = BaseSRegressor(learner=XGBRegressor())
cate_s = learner_s.fit_predict(X=X, treatment=treatment, y=y)
```

Generate data

Initialize learner
Fit and predict

S/ T/ X/ R Learner

```
from causalml.inference.meta import BaseSRegressor, BaseTRegressor, BaseXRegressor, BaseRRegressor

learner_s = LRSRegressor(learner=XGBRegressor())
learner_t = BaseTRegressor(learner=XGBRegressor())
learner_x = BaseXRegressor(learner=XGBRegressor())
learner_r = BaseRRegressor(learner=XGBRegressor())
cate_s = learner_s.fit_predict(X=X, treatment=treatment, y=y)
cate_t = learner_t.fit_predict(X=X, treatment=treatment, y=y)
cate_x = learner_x.fit_predict(X=X, treatment=treatment, y=y, p=e)
cate_r = learner_r.fit_predict(X=X, treatment=treatment, y=y, p=e)
```

Initialize learner

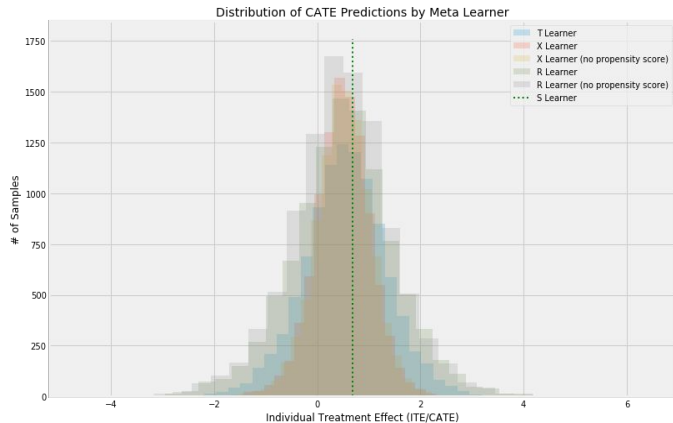
Fit and predict

Meta-Learners example:
[examples/meta_learners_with_synthetic_data.ipynb](#)

CausalML | CATE estimation example

Plot CATE predictions by learner

```
plt.hist(cate_t, alpha=alpha, bins=bins, label='T Learner')
plt.hist(cate_x, alpha=alpha, bins=bins, label='X Learner')
plt.hist(cate_r, alpha=alpha, bins=bins, label='R Learner')
plt.vlines(cate_s[0], 0, plt.axes().get_ylim()[1], ... .)
plt.title('Distribution of CATE Predictions by Meta Learner')
plt.xlabel('Individual Treatment Effect (ITE/CATE)')
plt.ylabel('# of Samples')
```



Estimate Average Treatment Effect (ATE)

```
ate_s = learner_s.estimate_ate(X=X, treatment=treatment, y=y)
print(ate_s)
print('ATE estimate: {:.03f}'.format(ate_s[0][0]))
print('ATE lower bound: {:.03f}'.format(ate_s[1][0]))
print('ATE upper bound: {:.03f}'.format(ate_s[2][0]))
```

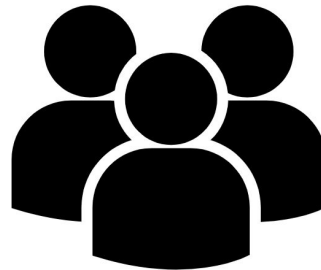
```
(array([0.6841716]), array([0.63612064]), array([0.73222256]))
ATE estimate: 0.684
ATE lower bound: 0.636
ATE upper bound: 0.732
```

CausalML | Value optimization

Knowing the CATE is often not sufficient to justify targeting populations if interventions are costly. Consider two scenarios:

1. The intervention costs more than the expected value of converting a customer
2. The customer is one that would convert anyway even in the absence of the intervention

These are some of the reasons why Causal ML contains modules for “value optimization”, ie for selecting populations for interventions in a way that optimizes ROI.



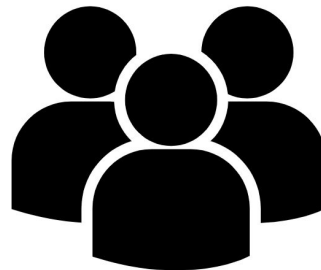
Probability of purchase under treatment: 0

Probability of purchase under control: 0

CATE: 0

Voucher: \$5

Cost of targeting: 0



Probability of purchase under treatment: 1

Probability of purchase under control: 1

CATE: 0

Voucher: \$5

Cost of targeting: -\$5

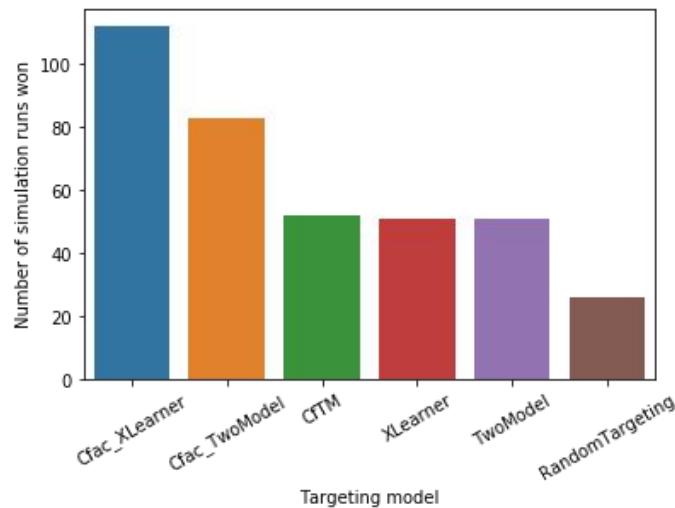
CausalML | Value optimization example

```
from causalml.optimize import CounterfactualValueEstimator
from causalml.optimize import get_treatment_costs, get_actual_value

# run the counterfactual calculation with TwoModel prediction
cve = CounterfactualValueEstimator(treatment=df_test['treatment_group_key'],
                                   control_name='control',
                                   treatment_names=conditions[1:],
                                   y_proba=y_proba,
                                   cate=tm_pred,
                                   value=conversion_value_array[test_idx],
                                   conversion_cost=cc_array[test_idx],
                                   impression_cost=ic_array[test_idx])

cve_best_idx = cve.predict_best()
cve_best = [conditions[idx] for idx in cve_best_idx]
actual_is_cve_best = df.loc[test_idx, 'treatment_group_key'] == cve_best
cve_value = actual_value.loc[test_idx][actual_is_cve_best].mean()

# plot the result
plt.bar(model_labels, model_scores)
```



Counterfactual Value Optimization example:
[examples/counterfactual_value_optimization.ipynb](#)

CausalML | Overview

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Propensity Score Methods

Sensitivity Analysis

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2SLS

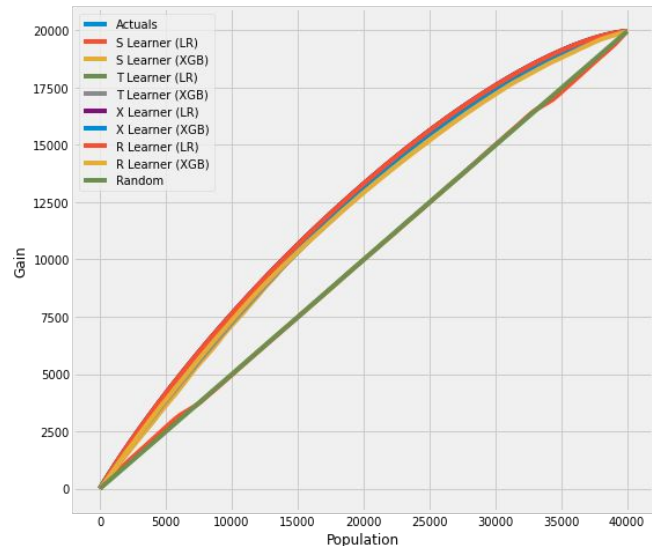
Doubly Robust IV

CausalML | Visualization: uplift curve

```
from causalmml.metrics import plot_gain, auuc_score
from causalmml.dataset import synthetic_data, simulate_nuisance_and_easy_treatment
from causalmml.synthetic import get_synthetic_preds_holdout, get_synthetic_auuc

# generate synthetic data for simulation
train_preds, valid_preds = get_synthetic_preds_holdout(simulate_nuisance_and_easy_treatment,
                                                         n=50000,
                                                         valid_size=0.2)

# generate gain AUUC values for validation data
get_synthetic_auuc(valid_preds)
```



Model and feature interpretation example:
[examples/feature_interpretations_example.ipynb](#)

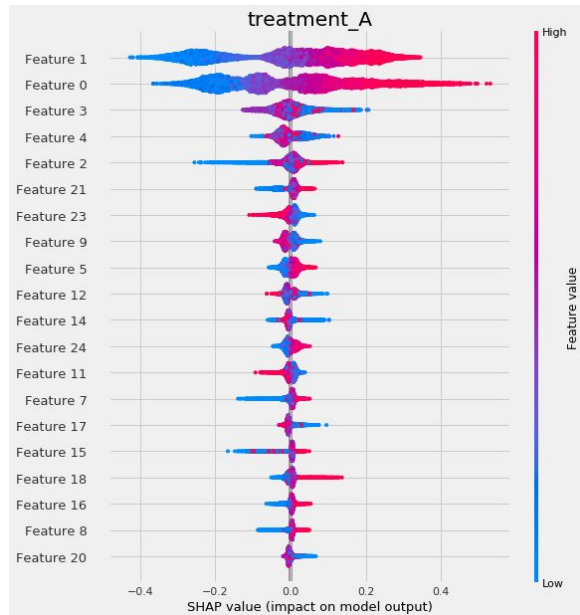
CausalML | Visualization: SHAP



```
from causalml.inference.meta import BaseSRegressor

y, X, treatment, tau, b, e = synthetic_data(mode=1, n=n_samples, p=n_features, sigma=0.5)
w_multi = np.array(['treatment_A' if x==1 else 'control' for x in treatment])

slearner = BaseSRegressor(LGBMRegressor(), control_name='control')
slearner_tau = slearner.fit_predict(X, w_multi, y)
slearner.plot_shap_values(X=X, tau=slearner_tau, features=feature_names)
```



Model and feature interpretation example:
[examples/feature_interpretations_example.ipynb](#)

CausalML | Data generation

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Classification dataset

```
from causalml.dataset import make_uplift_classification
# generate a synthetic dataset for classification uplift modeling problem
df, x_names = make_uplift_classification(n_samples=10000,
                                         treatment_name=['control', 'treatment1', 'treatment2'],
                                         y_name='conversion',
                                         n_classification_features=25,
                                         n_classification_informative=5,
                                         random_seed=2021)
```

Reproducibility

Flexible dataset customization

CausalML | Data generation

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                                       n_classification_informative=5,
                                       random_seed=2021)
```

df.head()

	treatment_group_key	x1_informative	x2_informative	x3_informative	x4_informative	x5_informative	x6_irrelevant	x7_irrelevant
0	control	0.796949	2.011955	1.010031	-0.082613	2.006405	0.853578	
1	treatment1	0.808755	0.027321	1.321761	-1.601562	0.701092	-0.943481	
2	control	0.092814	0.476592	-0.347588	0.319031	-0.523125	-0.142460	
3	control	0.769794	-2.382001	-0.353935	-1.643796	1.175124	1.302205	
4	control	0.753663	0.738282	-0.296090	-0.439421	0.067548	-0.178543	

df.treatment_group_key.value_counts()

```
treatment1    10000
control       10000
treatment2    10000
Name: treatment_group_key, dtype: int64
```

df.columns

```
Index(['treatment_group_key', 'x1_informative', 'x2_informative',
      'x3_informative', 'x4_informative', 'x5_informative', 'x6_irrelevant',
      'x7_irrelevant', 'x8_irrelevant', 'x9_irrelevant', 'x10_irrelevant',
      'x11_irrelevant', 'x12_irrelevant', 'x13_irrelevant', 'x14_irrelevant',
      'x15_irrelevant', 'x16_irrelevant', 'x17_irrelevant', 'x18_irrelevant',
      'x19_irrelevant', 'x20_irrelevant', 'x21_irrelevant', 'x22_irrelevant',
      'x23_irrelevant', 'x24_irrelevant', 'x25_irrelevant',
      'x26_uplift_increase', 'x27_uplift_increase', 'x28_increase_mix',
      'x29_uplift_increase', 'x30_uplift_increase', 'x31_increase_mix',
      'conversion', 'treatment_effect'],
      dtype='object')
```

CausalML | Data generation

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                                         y_name='conversion',
                                         n_classification_features=25,
                                         n_classification_informative=5,
                                         random_seed=2021)
```

Regression dataset

```
from causalml.dataset.regression import synthetic_data

y, x, treatment, tau, b, e = synthetic_data(mode=1, sigma=0.5,
                                           n=NUM_SAMPLES,
                                           P=NUM_FEATURES)
```

Support 5 modes of simulation ^{[1][2]}

^[1] Nie X. and Wager S. (2018) "Quasi-Oracle Estimation of Heterogeneous Treatment Effects"

^[2] Louizos et al. (2018) "Causal Effect Inference with Deep Latent-Variable Models"

CausalML | Propensity score methods

Modules

Data Generation Process

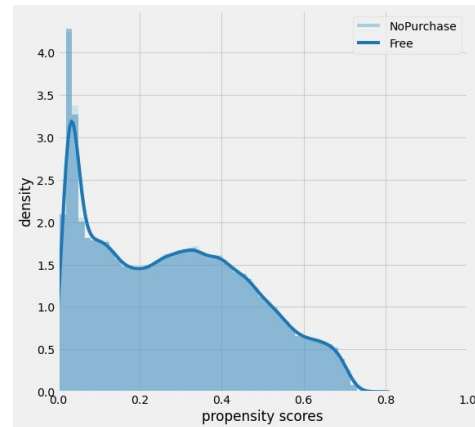
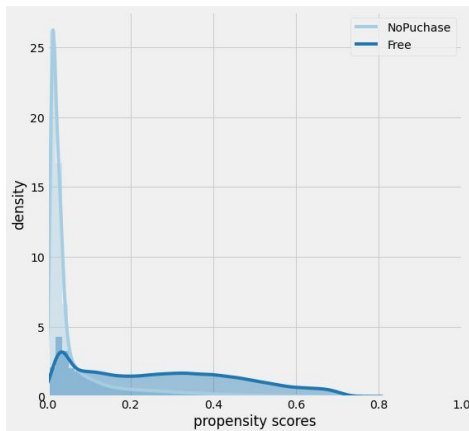
Feature Engineering

Propensity Score Methods

Sensitivity Analysis

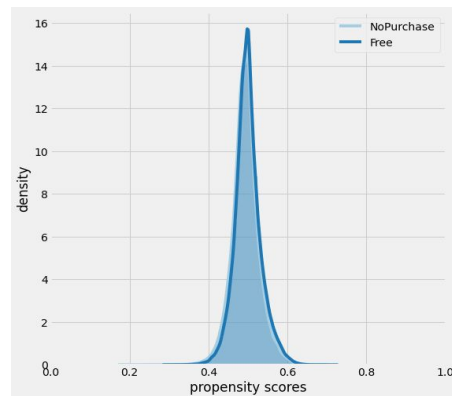
Causal Inference models

Visualization



1.Pre and Post PSM

2. Re-Calibration



CausalML | Propensity score methods

Propensity Score Matching

```
from causalml.match import NearestNeighborMatch, MatchOptimizer, create_table_one
from causalml.propensity import ElasticNetPropensityModel

clf.train(df_train[PROPENSITY_FEATURES], df_train[TREATMENT_COL])
df['pihat'] = clf.predict(df[PROPENSITY_FEATURES])
matcher = NearestNeighborMatch(caliper=0.1, replace=True)
df_matched = matcher.match(data=df, treatment_col=TREATMENT_COL, score_cols=['pihat'])
```

Re-calibrate propensity

```
from causalml.features import OneHotEncoder

ohe = OneHotEncoder(min_obs=df.shape[0] * 0.01)
X_cat = ohe.fit_transform(df_matched[ENCODING_COLS]).todense()
X = np.hstack([... .. , X_cat]) # transform propensity features properly
p_model = ElasticNetPropensityModel()
df_matched['pihat_re'] = p_model.fit_predict(X, df_matched['conversion'])

# print out SMD value for each feature after matching
create_table_one(df_matched, treatment_col=..., features=MATCHING_COVARIATES)
```

SMD values

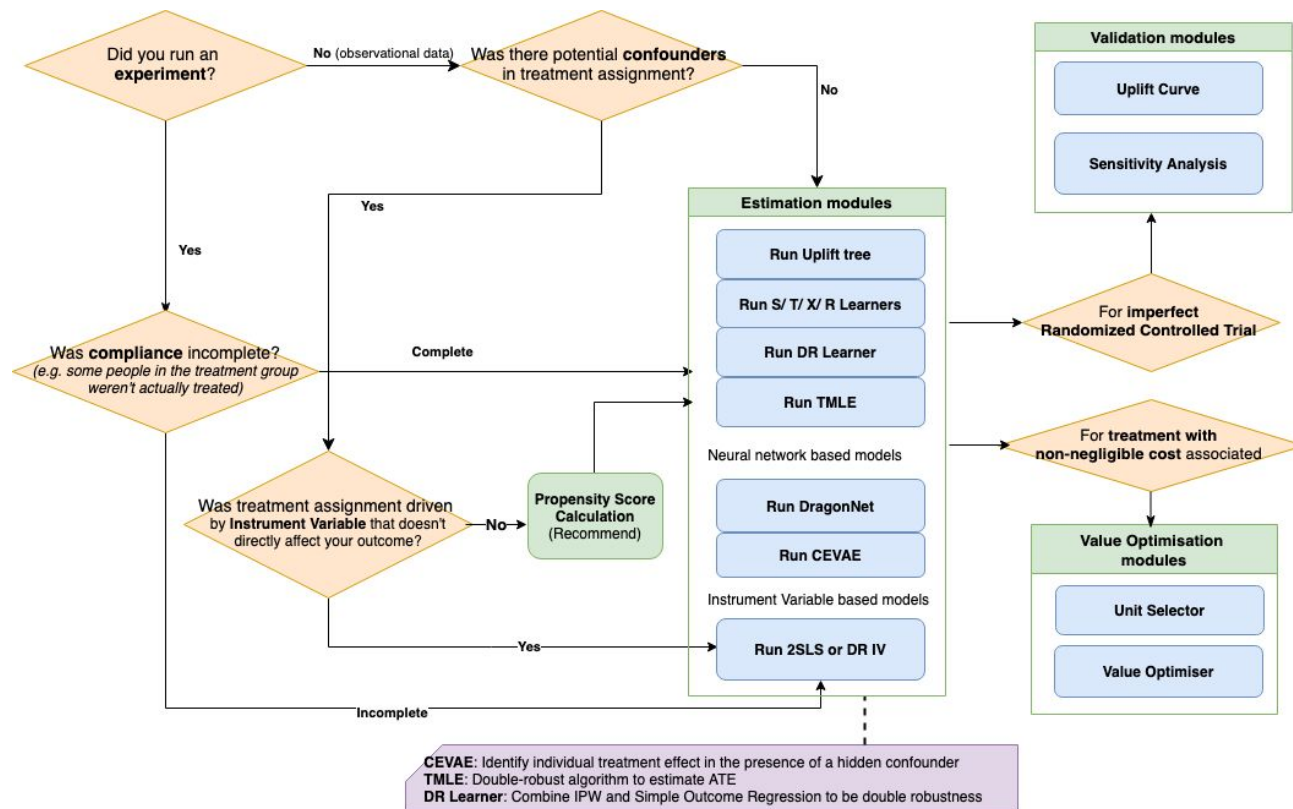
Variable	Control	Treatment	SMD
n	3656	3656	
pihat	0.07 (0.06)	0.07 (0.06)	0.0000
prob_features_11	0.39 (1.07)	0.36 (1.06)	-0.0295
prob_features_17	0.02 (0.81)	0.02 (0.84)	0.0021
prob_features_18	0.03 (0.82)	0.01 (0.82)	-0.0305
prob_features_19	-0.40 (0.79)	-0.35 (0.82)	0.0674
prob_features_20	0.56 (1.58)	0.41 (1.40)	-0.1040
prob_features_21	-0.07 (1.26)	-0.05 (1.05)	0.0162
prob_features_22	0.05 (0.94)	0.03 (0.86)	-0.0251
prob_features_23	0.61 (1.55)	0.46 (1.45)	-0.0941
prob_features_24	0.20 (1.08)	0.16 (1.06)	-0.0385

Propensity score matching: [causalml/causalml/match.py](https://causalml.github.io/causalml/match.py)

Sensitivity Analysis example: [examples/sensitivity_example_with_synthetic_data.ipynb](https://causalml.github.io/examples/sensitivity_example_with_synthetic_data.ipynb)

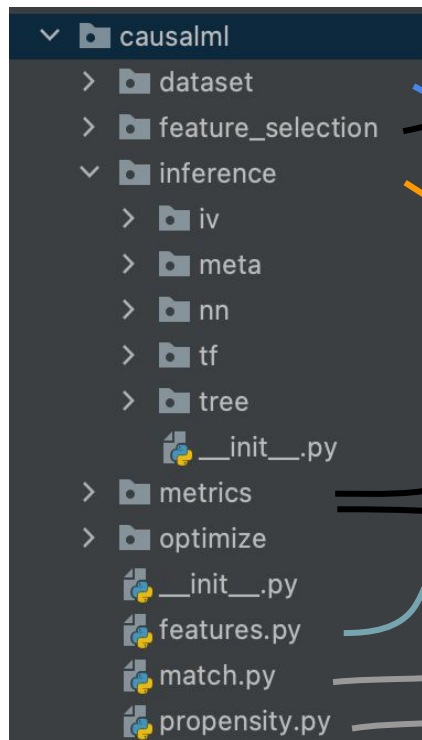
Summary

CausalML | User guide

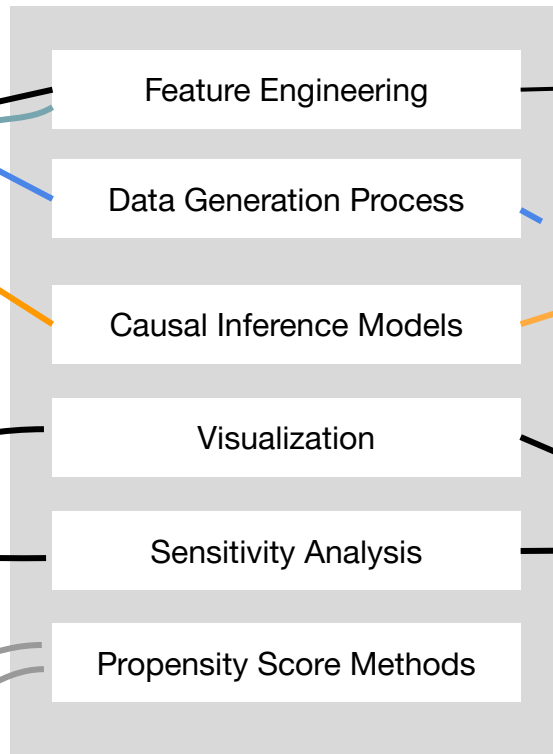


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Package structure



Modules and Key algorithms



Notebook examples

<https://github.com/uber/causalml/tree/master/examples>

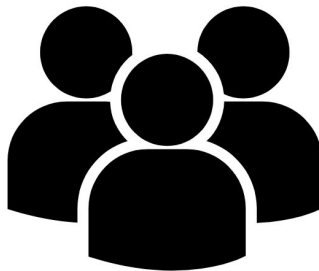
- feature_selection
 - meta_learners_with_synthetic_data
 - meta_learners_with_synthetic_data_multiple_treatment
 - uplift_trees_with_synthetic_data
 - dr_learner_with_synthetic_data
 - cevae_example
 - dragonnet_example
 - validation_with_tmle
 - uplift_tree_visualization
 - feature_interpretations_example
 - sensitivity_example_with_synthetic_data
- Optimize module**
- counterfactual_value_optimization
 - binary_policy_learner_example

Summary | Look forward to collaborating!



One-stop Shop

We **democratise uplift modeling methods** in academic paper and continue to add innovative in-house algorithms!



Dedicated support & Future collaborations

incubated for **long-term support** from Uber and community developers. **We welcome collaborations on package development and use cases!**

<https://github.com/uber/causalml#contributing>



Industrial Applications

We aim to tackle **real-world large scale data and industrial applications**.

→ **Let's dive into our Case Study section!**

Questions & Comments

Appendix

Appendix | References

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