Setup

```
gpu_info = !nvidia-smi
gpu_info = '\n'.join(gpu_info)
if gpu_info.find('failed') >= 0:
    print('Not connected to a GPU')
else:
    print(gpu_info)
```

Mon Mar 11 05:36:31 2024

NVID	IA-SMI	535.104.05	D	river	Version:	535.104.05	CUDA Versi	on: 12.2
GPU Fan	Name Temp	Perf	Persisten Pwr:Usage			- 1-		Uncorr. ECC Compute M. MIG M.
0 N/A	Tesla 66C	T4 P8	12W /	0ff 70W		0:00:04.0 01 iB / 15360Mi		0 Default N/A

+							+
-	Proc	esses:					
ĺ	GPU	GI	CI	PID	Type	Process name	GPU Memory
ĺ		ID	ID				Usage
-	=====	======	=======		=====	:======================================	
ĺ	No	running	processes	found			ĺ
+							+

```
from psutil import virtual_memory
ram_gb = virtual_memory().total / 1e9
print('Your runtime has {:.1f} gigabytes of available RAM\n'.format(ram_gb))
if ram_gb < 20:
  print('Not using a high-RAM runtime')
  print('You are using a high-RAM runtime!')
    Your runtime has 13.6 gigabytes of available RAM
    Not using a high-RAM runtime
!pip install chemprop
!pip install rdkit-pypi # should be included in above after Chemprop v1.6 release
import chemprop
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.offsetbox import AnchoredText
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.decomposition import PCA
```

requirement atteauy satistieu: imagesize in /usi/tocat/tip/pythono.im/uist-packages (from sphiinx/=0.1.2->chemprop Requirement already satisfied: requests>=2.5.0 in /usr/local/lib/python3.10/dist-packages (from sphinx>=3.1.2->ch Requirement already satisfied: protobuf>=3.20 in /usr/local/lib/python3.10/dist-packages (from tensorboardX>=2.0-Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from torch>=1.4.0->chemprop) Requirement already satisfied: typing-extensions in /usr/local/lib/python3.10/dist-packages (from torch>=1.4.0->c Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages (from torch>=1.4.0->chemprop) (1. Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (from torch>=1.4.0->chemprop) (2 Requirement already satisfied: triton==2.1.0 in /usr/local/lib/python3.10/dist-packages (from torch>=1.4.0->chemp Collecting typing-inspect>=0.7.1 (from typed-argument-parser>=1.6.1->chemprop) Downloading typing_inspect-0.9.0-py3-none-any.whl (8.8 kB)

Collecting docstring-parser>=0.15 (from typed-argument-parser>=1.6.1->chemprop)

Downloading docstring_parser-0.15-py3-none-any.whl (36 kB)

Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from Jinja2>=3.0->flas Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests>=2.5.0->sph Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests>=2.5. Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests>=2.5. Collecting mypy-extensions>=0.3.0 (from typing-inspect>=0.7.1->typed-argument-parser>=1.6.1->chemprop)

Downloading mypy_extensions-1.0.0-py3-none-any.whl (4.7 kB)

Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.10/dist-packages (from sympy->torch>=1.4.0-Building wheels for collected packages: typed-argument-parser

Building wheel for typed-argument-parser (setup.py) ... done
Created wheel for typed-argument-parser: filename=typed_argument_parser-1.9.0-py3-none-any.whl size=25615 sha25 Stored in directory: /root.cache/pip/wheels/f0/94/0f/9539f578bed7e1bd423c702e403712f5ee8989f831a71db000 Successfully built typed-argument-parser

Installing collected packages: tensorboardX, rdkit, mypy-extensions, docstring-parser, typing-inspect, typed-argu Successfully installed chemprop-1.6.1 docstring-parser-0.15 mypy-extensions-1.0.0 pandas-flavor-0.6.0 rdkit-2023. Collecting rdkit-pypi

Downloading rdkit_pypi-2022.9.5-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (29.4 MB) - 29.4/29.4 MB 53.7 MB/s eta 0:00:00

Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from rdkit-pypi) (1.25.2) Requirement already satisfied: Pillow in /usr/local/lib/python3.10/dist-packages (from rdkit-pypi) (9.4.0) Installing collected packages: rdkit-pypi

Successfully installed rdkit-pypi-2022.9.5

from IPython.core.interactiveshell import InteractiveShell InteractiveShell.ast_node_interactivity = "all"

hiv_df = pd.read_csv("HIV.csv") hiv_df.head()

	smiles	activity	HIV_active
0	CCC1 = [O+][Cu-3]2([O+] = C(CC)C1)[O+] = C(CC)CC(CC)	CI	0
1	C(=Cc1ccccc1)C1 = [O+][Cu-3]2([O+] = C(C=Cc3ccccc3	CI	0
2	CC(=O)N1c2cccc2Sc2c1ccc1cccc21	CI	0
3	Nc1ccc(C=Cc2ccc(N)cc2S(=O)(=O)O)c(S(=O)(=O)O)c1	CI	0
4	O=S(=O)(O)CCS(=O)(=O)O	CI	0

hiv_df.describe()

	HIV_active
count	41127.000000
mean	0.035086
std	0.184001
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

```
unique_values = hiv_df['HIV_active'].unique()
print(f"Unique values in 'HIV_active': {unique_values}")
    Unique values in 'HIV_active': [0 1]
unique_values = hiv_df['smiles'].unique()
print(f"Unique values in 'smiles': {unique_values}")
```

print(f"length of uniqe value: {len(unique_values)}")

Unique values in 'smiles': ['CCC1=[0+][Cu-3]2([0+]=C(CC)C1)[0+]=C(CC)CC(CC)=[0+]2'
 'C(=Cc1cccc1)C1=[0+][Cu-3]2([0+]=C(C=Cc3cccc3)CC(c3cccc3)=[0+]2)[0+]=C(c2cccc2)C1'
 'CC(=0)N1c2cccc2Sc2c1ccc1ccccc21' ...
 'Cc1ccc(N2C(=0)C3c4[nH]c5ccccc5c4C4CCC(C(C)(C)C)CC4C3C2=0)cc1'
 'Cc1ccc(N2C(=0)C3c4[nH]c5ccccc5c4C4CCC(C(C)(C)C)CC4C3C2=0)c1'
 'CCCCCC=C(c1cc(C1)c(0C)c(-c2nc(C)no2)c1)c1cc(C1)c(0C)c(-c2nc(C)no2)c1']
length of uniqe value: 41127

Filter rows where 'your_column' is not equal to 1 or 0
filtered_df = hiv_df[(hiv_df['HIV_active'] != 1) & (hiv_df['HIV_active'] != 0)]
filtered_df

smiles activity HIV_active

Filter rows where 'target_column' is equal to 1h
hiv_df_filtered_active = hiv_df[hiv_df['HIV_active'] == 1]
hiv_df_filtered_active

	smiles	activity	HIV_active
11	O=C(O)Cc1ccc(SSc2ccc(CC(=O)O)cc2)cc1	CM	1
16	NNP(=S)(NN)c1cccc1	CM	1
80	O=Nc1ccc(O)c(N=O)c1O	CM	1
203	${\sf Oc1ccc}({\sf Cl}){\sf cc1C}({\sf c1cc}({\sf Cl}){\sf ccc1O}){\sf C}({\sf Cl})({\sf Cl}){\sf Cl}$	CM	1
234	NNC(=O)c1ccccc1SSc1ccccc1C(=O)NN	CM	1
41090	Cc1cn(COCCCOCC(=O)c2ccccc2)c(=O)[nH]c1=O	CM	1
41092	$\label{eq:condition} \textbf{Cc1cn}(\textbf{C2CC3C}(\textbf{COC}(\textbf{CCC}[\textbf{Se}]\textbf{c4ccccc4})\textbf{N3O})\textbf{O2})\textbf{c}(=\textbf{O})[$	CM	1
41093	${\tt Cc1cn(C2CC3C(COC(CCCC[Se]c4ccccc4)N3O)O2)c(=O)}$	CM	1
41098	Cc1cn(C2CC3C(COC(CC[Se]C#N)N3O)O2)c(=O)[nH]c1=O	CM	1
41099	C[Se]CCC1OCC2OC(n3cc(C)c(=O)[nH]c3=O)CC2N1O	CA	1

1443 rows × 3 columns

Filter rows where 'target_column' is equal to 1h
hiv_df_filtered_inactive = hiv_df[hiv_df['HIV_active'] == 0]
hiv_df_filtered_inactive = hiv_df_filtered_inactive.sample(n=1500, axis=0, random_state=42)
hiv_df_filtered_inactive

	smiles	activity	HIV_active
2428	O=C1c2cccc2-c2nc3ccccc3nc21	CI	0
6197	O=C(CSc1cc(-c2ccc(Cl)cc2)s[s+]1)c1ccccc1	CI	0
17138	O=C(C=Nc1ccccc1C(=O)O)c1cccc1	CI	0
12261	CCCCCCCCCCCCCCC[N+](C)(C)Cc1ccc(C[N+](C)(C)	CI	0
3588	N#CSC1CCCCCC1SC#N	CI	0
18477	CC(=O)OC1(C#N)CC2OC1C1C2N1C(=O)OC(C)(C)C	CI	0
1189	CCOC(=0)C1Cc2cc(C)c(C)cc2N(C)C1=0	CI	0
36657	CCOC(=O)N1CCN(c2ccc3c(C)cc(C)nc3n2)CC1	CI	0
27919	CN(C)C=Nc1ccc2c3c(cccc13)-c1ccccc1-2	CI	0
13479	CCC1CC2CC3c4[nH]c5ccc(OC)cc5c4CCN(C2)C13.CI	CI	0

1500 rows × 3 columns

hiv_df_sampled = pd.concat([hiv_df_filtered_active, hiv_df_filtered_inactive], axis=0, ignore_index=True)
hiv_df_sampled

	smiles	activity	HIV_active
0	O=C(O)Cc1ccc(SSc2ccc(CC(=O)O)cc2)cc1	CM	1
1	NNP(=S)(NN)c1ccccc1	CM	1
2	O=Nc1ccc(O)c(N=O)c1O	CM	1
3	${\sf Oc1ccc}({\sf CI}){\sf cc1C}({\sf c1cc}({\sf CI}){\sf ccc1O}){\sf C}({\sf CI})({\sf CI}){\sf CI}$	CM	1
4	NNC(=O)c1ccccc1SSc1ccccc1C(=O)NN	CM	1
2938	CC(=O)OC1(C#N)CC2OC1C1C2N1C(=O)OC(C)(C)C	CI	0
2939	CCOC(=0)C1Cc2cc(C)c(C)cc2N(C)C1=O	CI	0
2940	CCOC(=O)N1CCN(c2ccc3c(C)cc(C)nc3n2)CC1	CI	0
2941	CN(C)C=Nc1ccc2c3c(cccc13)-c1ccccc1-2	CI	0
2942	CCC1CC2CC3c4[nH]c5ccc(OC)cc5c4CCN(C2)C13.Cl	CI	0

2943 rows × 3 columns

Randomly shuffle rows

hiv_df_sampled = hiv_df_sampled.sample(frac=1, random_state=42)

hiv_df_sampled.head()

	smiles	activity	HIV_active
240	Cc1cc2c(c(=O)o1)C1=S(SC(c3ccccc3)=C1)S2	CM	1
2325	N#CN1CCC=C(c2cc3ccccc3[nH]2)C1	CI	0
1676	CCC1SC(C)C(=O)NC1=O	CI	0
1952	O=C1CC2(CCN(Cc3ccccc3)CC2)CC(=O)N1	CI	0
677	CC(=O)OC1SC(c2c(F)cccc2F)n2c1nc1ccccc12	CM	1

hiv_df_sampled.to_csv('HIV_2.csv', index=False) # .drop(['activity'], axis=1).
hiv_df_sampled_2 = pd.read_csv("HIV_2.csv")
hiv_df_sampled_2.head()

hiv_df_sampled_2.tail()

	smiles	activity	HIV_active	•
0	Cc1cc2c(c(=O)o1)C1=S(SC(c3cccc3)=C1)S2	CM	1	
1	N#CN1CCC=C(c2cc3ccccc3[nH]2)C1	CI	C)
2	CCC1SC(C)C(=O)NC1=O	CI	C)
3	O=C1CC2(CCN(Cc3ccccc3)CC2)CC(=O)N1	CI	C)
4	CC(=O)OC1SC(c2c(F)cccc2F)n2c1nc1ccccc12	CM	1	
		smiles	activity	HIV_active
29	38 O=C(CS)f	smiles	activity	HIV_active 0
	O=C(CS)N O=C(Nc1ccc(N=Nc2ccc(S(=O)(=O)O)cc2)c	Nc1cccc(O)c1	CI	<u>-</u>
29		Nc1ccc(O)c1	CI	0
29 29	39 O=C(Nc1ccc(N=Nc2ccc(S(=O)(=O)O)cc2)c 40 NC(=O)CCN(CCC(N)=	Nc1ccc(O)c1	CI CM CI	0

```
arguments = [
     '--data_path', 'HIV.csv',
    '--dataset_type', 'classification',
    '--save_dir', 'test_checkpoints_multimolecule', '--epochs', '30',
    '--save_smiles_splits',
    '--quiet',
    '--batch_size', '64',
     '--ignore_columns', 'activity',
     '--depth', '5',
    '--hidden_size', '300'
]
args = chemprop.args.TrainArgs().parse_args(arguments)
mean_score, std_score = chemprop.train.cross_validate(args=args, train_func=chemprop.train.run_training)
      82%|
                       422/515 [01:38<00:22,
                                                4.18it/s]
                                [01:38<00:16,
      82%
                       424/515
                                                5.45it/sl
      83%
                       425/515
                                [01:38<00:15,
                                                5.95it/s]
      83%
                       426/515
                                [01:39<00:21,
                                                4.14it/s]
      83%|
                       427/515
                                [01:39<00:19,
                                                4.51it/s]
                       428/515
                                [01:39<00:19,
      83%
                                                4.54it/sl
      83%
                       429/515 [01:40<00:39,
                                                2.15it/sl
      84%
                       431/515
                                [01:40<00:24,
                                                3.41it/s]
      84%
                       432/515
                                [01:40<00:20,
                                                4.01it/sl
                                [01:40<00:18,
      84%
                       433/515
                                                4.50it/sl
      84%
                       434/515
                                [01:41<00:27,
                                                2.97it/s]
      84%
                       435/515
                                [01:41<00:21,
                                                3.64it/s]
      85% İ
                       436/515
                                [01:41<00:18,
                                                4.35it/s
      85%
                       437/515
                                [01:42<00:25,
                                                3.02it/sl
      85%
                       439/515
                                [01:42<00:15,
                                                4.83it/s]
      86%
                       441/515
                                [01:42<00:11,
                                                6.47it/s]
      86%
                       443/515
                                [01:43<00:14,
                                                4.98it/sl
      86%
                       444/515
                                [01:43<00:13,
                                                5.34it/s]
      86%|
                       445/515
                                [01:43<00:18,
                                                3.75it/s
      87%
                       447/515
                                [01:44<00:12,
                                                5.28it/s]
      87%
                                [01:44<00:09.
                       449/515
                                                6.67it/sl
      87%
                       450/515
                                [01:44<00:14,
                                                4.34it/s]
                       452/515
      88%
                                [01:44<00:10,
                                                5.75it/s]
      88%
                       453/515
                                [01:45<00:20,
                                                2.99it/s]
      88%
                       455/515
                                                4.25it/s]
                                [01:46<00:14,
      89%
                       457/515
                                [01:46<00:10,
                                                5.65it/s]
      89%
                       459/515
                                [01:46<00:13,
                                                4.27it/s]
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                       460/515
                                [01:46<00:11,
                                                4.78it/sl
                                [01:47<00:14,
      90%
                       461/515
                                                3.63it/sl
      90%
                       463/515
                                [01:47<00:10,
                                                5.14it/sl
      90%
                       465/515
                                [01:47<00:07,
                                                6.62it/s]
      91%
                       467/515
                                [01:48<00:09,
                                                5.32it/s]
      91%|
                       469/515
                                [01:48<00:10,
                                                4.35it/s]
      92%
                       472/515
                                [01:49<00:06,
                                                6.36it/s]
      92%
                       474/515
                                [01:49<00:07,
                                                5.13it/s]
                       476/515
                                [01:49<00:06.
      92%
                                                6.18it/sl
      93%
                       477/515
                                [01:50<00:09.
                                                4.04it/sl
      93%
                       479/515
                                [01:50<00:06,
                                                5.30it/s]
      93%
                       481/515
                                [01:50<00:05,
                                                6.61it/s]
                                [01:51<00:06,
      94%1
                       483/515
                                                5.12it/s
      94%
                       484/515
                                [01:51<00:05]
                                                5.56it/s]
      94%|
                       485/515
                                [01:52<00:12,
                                                2.41it/sl
      95%
                       487/515
                                [01:52<00:07,
                                                3.58it/s]
      95%
                       489/515
                                [01:53<00:05.
                                                4.60it/sl
      95%
                       491/515
                                [01:54<00:07,
                                                3.25it/s]
      96%
                       492/515
                                [01:54<00:06,
                                                3.56it/s]
      96%1
                       493/515
                                [01:55<00:09.
                                                2.42it/sl
      96%
                       495/515
                                [01:55<00:05,
                                                3.53it/s]
      97%
                       497/515
                                [01:55<00:03,
                                                4.69it/s]
      97%|
                       498/515
                                [01:56<00:05,
                                                3.38it/s]
      97%
                       499/515
                                [01:56<00:04.
                                                3.85it/sl
      97%
                       500/515
                                [01:56<00:03.
                                                4.49it/sl
      97%
                       501/515
                                [01:57<00:05,
                                                2.42it/s]
      98%
                       506/515
                                [01:57<00:01,
                                                6.06it/s]
                       509/515 [01:57<00:00,
      99%
                                                7.72it/sl
                       514/515 [01:57<00:00, 12.06it/s]
     100%
       0%|
                     | 0/65 [00:00<?, ?it/s]
mean_score, std_score
     (0.7778557998980004, 0.0)
```

 $https://colab.research.google.com/drive/1XZtJQn6BnxthuK1DDLR482xj_djrGBKD\#scrollTo=_5WAeovcolqi\&uniqifier=1\&printMode=true$

```
bp_df = pd.read_csv("BBBP.csv")
bp_df.head()
```

```
smiles
       num
                          name
                                p np
    0
                     Propanolol
                                    1
                                                        [CI].CC(C)NCC(O)COc1cccc2cccc12
          1
                                               C(=O)(OC(C)(C)C)CCC1ccc(cc1)N(CCCI)CCCI
     1
          2
             Terbutylchlorambucil
                                    1
    2
          3
                         40730
                                       c12c3c(N4CCN(C)CC4)c(F)cc1c(c(C(O)=O)cn2C(C)CO...
     3
          4
                             24
                                    1
                                                     C1CCN(CC1)Cc1cccc(c1)OCCCNC(=O)C
                                            Cc1onc(c2cccc2Cl)c1C(=O)N[C@H]3[C@H]4SC(C)
                      cloxacillin
                                    1
    4
          5
             View recommended plots
Next steps:
```

bp_df.tail()

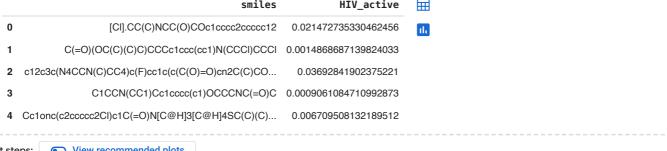
```
smiles
            num
                                name
                                      p_np
                                             C1=C(CI)C(=C(C2=C1NC(=O)C(N2)=O)[N+](=O)
     2045 2049
                              licostinel
                                                                               [O-])CI
                                             [C@H]3([N]2C1 = C(C(=NC=N1)N)N = C2)[C@@H]
                 ademetionine(adenosyl-
     2046
           2050
                           methionine)
                                                                           [O+]1=N[N]
      2047
           2051
                             mesocarb
                                             (C=C1[N-]C(NC2=CC=CC=C2)=O)C(CC3=CC=...
                                                C1=C(OC)C(=CC2=C1C(=IN+I(C(=C2CC)C)
      bp_df.drop(['num', 'name', 'p_np'], axis=1).to_csv('BBBP_2.csv', index=False)
bp_df_2 = pd.read_csv("BBBP_2.csv")
bp_df_2.head()
bp_df_2.tail()
```

```
\overline{\mathbf{H}}
                                               smiles
0
                    [CI].CC(C)NCC(O)COc1cccc2cccc12
           C(=O)(OC(C)(C)C)CCCc1ccc(cc1)N(CCCI)CCCI
1
2
   \verb|c12c3c(N4CCN(C)CC4)c(F)cc1c(c(C(O)=O)cn2C(C)CO...|
3
                 C1CCN(CC1)Cc1cccc(c1)OCCCNC(=O)C
   Cc1onc(c2cccc2Cl)c1C(=O)N[C@H]3[C@H]4SC(C)(C)...
                                                     smiles
2045
           C1=C(CI)C(=C(C2=C1NC(=O)C(N2)=O)[N+](=O)[O-])CI
2046
      [C@H]3([N]2C1=C(C(=NC=N1)N)N=C2)[C@@H]([C@@H](...
       [O+]1=N[N](C=C1[N-]C(NC2=CC=CC=C2)=O)C(CC3=CC=...
2047
        C1=C(OC)C(=CC2=C1C(=[N+](C(=C2CC)C)[NH-])C3=CC...
2048
2049
         [N+](=NCC(=O)N[C@@H]([C@H](O)C1=CC=C([N+]([O-]...
```

```
arguments = [
   '--test_path', 'BBBP_2.csv',
   '--preds_path', 'BBBP_preds.csv',
   '--checkpoint_dir', 'test_checkpoints_multimolecule'
]
args = chemprop.args.PredictArgs().parse_args(arguments)
preds = chemprop.train.make_predictions(args=args)
```

```
Copy of chemprop_colab_demo.ipynb - Colaboratory
נשו:שא: שב : שב warning: ווטנ ופוווטving nyarogen atom without neighbors
[07:04:30] WARNING: not removing hydrogen atom without neighbors
[07:04:31] WARNING: not removing hydrogen atom without neighbors
[07:04:31] WARNING: not removing hydrogen atom without neighbors
usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will cre/
 warnings.warn(_create_warning_msg(
Test size = 2,039
0% | 0/1 [00:00<?, ?it/s]Loading pretrained parameter "encoder.o.cached_zero_vector". Loading pretrained parameter "encoder.encoder.o.W_i.weight".
Loading pretrained parameter "encoder.encoder.0.W_h.weight".
Loading pretrained parameter "encoder.encoder.0.W_o.weight".
Loading pretrained parameter "encoder.encoder.0.W_o.bias".
Loading pretrained parameter "readout.1.weight".
Loading pretrained parameter "readout.1.bias".
Loading pretrained parameter "readout.4.weight".
Loading pretrained parameter "readout.4.bias".
Moving model to cuda
                | 0/41 [00:00<?, ?it/s]
  0%1
  2%||
                 1/41 [00:02<01:21, 2.04s/it]
 10%|
                 4/41 [00:02<00:22,
                                      1.63it/s]
 22%
                 9/41 [00:03<00:08,
                                      3.57it/s]
                 12/41 [00:03<00:06,
 29% i
                                       4.39it/sl
 37%
                 15/41 [00:03<00:04.
                                       6.19it/sl
                 17/41 [00:04<00:04,
 41%|
                                       5.47it/sl
 49%
                 20/41 [00:04<00:03,
                                       6.22it/s]
                 23/41 [00:04<00:02,
 56%
                                       8.27it/sl
                 25/41 [00:05<00:02,
 61%|
                                       7.12it/s]
 68% II
                  28/41 [00:05<00:01,
                                       8.08it/sl
                 33/41 [00:05<00:00, 10.42it/s]
 80%1
                 36/41 [00:05<00:00, 12.54it/s]
 88%
                 1/1 [00:06<00:00, 6.40s/it] Saving predictions to BBBP_preds.csv
100%|
Elapsed time = 0:00:07
                                          smiles
                                                           HIV_active
                                                                         扁
0
                  [CI].CC(C)NCC(O)COc1cccc2cccc12
                                                  0.021472735330462456
 1
          C(=O)(OC(C)(C)C)CCCc1ccc(cc1)N(CCCI)CCCI 0.0014868687139824033
```

bp_preds_df = pd.read_csv("BBBP_preds.csv") bp_preds_df.head()

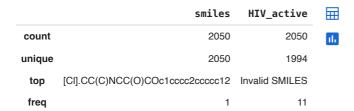


Next steps: View recommended plots

bp_preds_df.tail()

```
smiles
                                                                  HIV active
                                                                                 扁
2045
         C1=C(CI)C(=C(C2=C1NC(=O)C(N2)=O)[N+](=O)[O-])CI 0.0041548567824065685
      [C@H]3([N]2C1=C(C(=NC=N1)N)N=C2)[C@@H]([C@@H]
2046
                                                         0.015147102996706963
                                             [O+]1=N[N]
2047
                                                         0.004494475666433573
              (C=C1[N-]C(NC2=CC=CC=C2)=O)C(CC3=CC=...
                  C1=C(OC)C(=CC2=C1C(=[N+](C(=C2CC)C)
2048
                                                          0.05315469577908516
                                          [NH-1)C3=CC...
```

bp_preds_df.describe()



bp_preds_df = bp_preds_df[bp_preds_df['HIV_active'] != "Invalid SMILES"]
bp_preds_df.describe()

	HIV_active	smiles	
ıl.	2039	2039	count
	1993	2039	unique
	0.0003313531633466482	[CI].CC(C)NCC(O)COc1cccc2ccccc12	top
	3	1	freq

bp_preds_df['HIV_active'] = bp_preds_df['HIV_active'].astype(float)

 $bp_preds_df['HIV_active_2'] = bp_preds_df['HIV_active']. apply(lambda x: 1 if x > 0.8 else 0) \\ bp_preds_df.head()$

	smiles	HIV_active	HIV_active_2	\blacksquare
0	[CI].CC(C)NCC(O)COc1cccc2ccccc12	0.021473	0	ılı
1	C(=O)(OC(C)(C)C)CCCc1ccc(cc1)N(CCCI)CCCI	0.001487	0	
2	$\mathtt{c12c3c}(N4CCN(C)CC4)c(F)cc1c(c(C(O)\!\!=\!\!O)cn2C(C)CO$	0.036928	0	
3	C1CCN(CC1)Cc1cccc(c1)OCCCNC(=O)C	0.000906	0	
4	Cc1onc(c2cccc2Cl)c1C(=O)N[C@H]3[C@H]4SC(C) (C)	0.006710	0	

bp_preds_df.describe()

	HIV_active	HIV_active_2	
count	2.039000e+03	2039.000000	ıl.
mean	2.598170e-02	0.001962	
std	6.617616e-02	0.044259	
min	4.265374e-10	0.000000	
25%	3.987846e-03	0.000000	
50%	1.050125e-02	0.000000	
75%	2.310448e-02	0.000000	
max	8.798995e-01	1.000000	

Filter rows where 'target_column' is equal to 1
bp_preds_df_filtered = bp_preds_df[bp_preds_df['HIV_active_2'] == 1]
bp_preds_df_filtered

03/2024, 12:55		(Copy of chemprop_c	olab_demo.	.ipynb -	Colaboratory
			1 to 4 of 4 e	entries Filte	er L	?
index		smiles	HIV_ac		HIV_acti	
11		2C[C@H](F)[C@@H]	0.84600210			1
	(CO)O2)C(=O)N	C1=O :[C@@H](O1)n2cnc3C(=O)N=CNc23				1
		,[C@@H](O1)H2CHC3C(=O)N=CNC23 H]2O[C@H](CO)C=C2)C(=O)NC1=O				1
		C=C1)[C@H]2CC[C@@H](CO)O2	0.87989950			1
Show	25 V per pag	je				
11.						
Like_w	hat vou see? Visit	the data table notebook to learn mo	ore about interactive	tables		
Next steps	• View red	commended plots				
smiles_to_	_check = bp_p	reds_df_filtered['smiles'].	to_list()			
	- .		_			
hiv_df_sam	npled_2[hiv_d	f_sampled_2['smiles'].isin(smiles_to_chec	k)]		
NameE	rror		aceback (most	 recent ca	ll las	 st)
<ipyt< td=""><td>hon-input-29-</td><td><u>-97b3985eab54></u> in <cell lin<="" td=""><td>e: 1>()</td><td></td><td></td><td></td></cell></td></ipyt<>	hon-input-29-	<u>-97b3985eab54></u> in <cell lin<="" td=""><td>e: 1>()</td><td></td><td></td><td></td></cell>	e: 1>()			
>	1 hiv_df_sam	npled_2[hiv_df_sampled_2['s	miles'].isin(s	niles_to_	check	1
NameE	rror: name 'h	niv_df_sampled_2' is not de	fined			
hiv_df[hiv	/_df['smiles']].isin(smiles_to_check)]				
cm.	iles activity	/ HIV_active				
5111.	ites activity	/ hiv_active				
bp_df[bp_d	df['smiles'].:	isin(smiles_to_check)]				
	num name	e p_np			lles	
11	12 alovudine	e 1 CC1=CN([C@H]2C[C@F	1](F)[C@@H](CO)C)2)C(=O)NC	1=O	d.
289	291 Didanosine	o OC[C@@H]1CC[0	C@@H](O1)n2cnc3	C(=O)N=CN	Nc23	
319	321 Stavudine	e 1 CC1=CN([C@@H]2O[C@H](CO)C=C	2)C(=O)NC	1=0	
346	348 Zalcitabine	e 1 NC1=NC(=O)N	 (C=C1)[C@H]2CC	<u>.</u> റതതലുഗ്ര))O2	
340	240 Zaioitabilie	3 1 1401-140(-0)14	(0=01)[0@11]200[0@@11](00	0)02	
		//	,			
<pre>bp_df_fina bp_df_fina</pre>		(bp_df[bp_df['smiles'].isir	i(smiles_to_che	ck)], bp_	_preds	_df_filtered, on='smiles')
bp_d1_11110						
nı	ım name	p_np smile	es HIV_active	HIV_acti	ve_2	
		CC1=CN([C@H]2C[C@H](F)			•
0	12 alovudine	1 [C@@	H] 0.846002		1	
		(CO)O2)C(=O)NC1=	·O			
1 29	91 Didanosine	OC[C@@H]1CC[C@@			1	
		(O1)n2cnc3C(=O)N=CNc2	23			
	04 04	CC1=CN([C@@H]2O[C@	H]			
Next steps	: View red	commended plots				
bp_df_fina	al.to_csv('HI\	<pre>V_result.csv', index=False)</pre>	1			
		substances.csv")				
sub_df.hea	ad()					
	_3 1	.i	am#1	—		
	zinc_i		smiles			
0 ZI	NC000000000002	7 N[C@@H](CCc1ccc(N(CCCI)C	CCI)cc1)C(=O)O	ıl.		
1 ZI	NC000016090786	6 N[C@H](CCc1ccc(N(CCCI)C	CCI)cc1)C(=O)O			
	NC000001763088					
2 ZI	140000001703088	o New House to the control of the co	,001,001,0(±0)0			

N[C@@H](Cc1ccc(N(CCCI)CCCI)cc1)C(=O)O

 ${\bf 3} \quad {\sf ZINC000002033385} \quad {\sf N[C@@H](CCCc1ccc(N(CCCI)CCCI)cc1)C(=O)O} \\$

4 ZINC00000001673

Next steps:

View recommended plots

```
sub df.tail()
                 zinc_id
                                                     smiles
                                                               翩
     46 ZINC000196349655
                              O=C(O)CCSc1ccc(N(CCCI)CCCI)cc1
     47 ZINC000064454242
                                 N=NCCCc1ccc(N(CCCI)CCCI)cc1
     48 ZINC000005161807
                            O=C(O)C/C=C/c1ccc(N(CCCI)CCCI)cc1
     49 ZINC000001682294
                              O=C(O)CCOc1ccc(N(CCCI)CCCI)cc1
     50 ZINC000079564304 O=C(O)CNC(=O)c1ccc(N(CCCI)CCCI)cc1
 sub_df.info()
     <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 51 entries, 0 to 50
    Data columns (total 2 columns):
                   Non-Null Count Dtype
     #
         Column
         zinc_id 51 non-null
                                    object
         smiles
                   51 non-null
                                    object
     1
    dtypes: object(2)
    memory usage: 944.0+ bytes
 arguments = [
      '--test_path', 'substances.csv',
      '--preds_path', 'substances_preds.csv',
      '--checkpoint_dir', 'test_checkpoints_multimolecule', '--smiles_columns', 'smiles'
 1
 args = chemprop.args.PredictArgs().parse_args(arguments)
 preds = chemprop.train.make_predictions(args=args)
    Loading training args
    Setting molecule featurization parameters to default.
    Loading data
    51it [00:00, 39141.72it/s]
                   51/51 [00:00<00:00, 69586.70it/s]
    100%
    /usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will cre
      warnings.warn(_create_warning_msg(
    Validating SMILES
    Test size = 51
    0%| | 0/1 [00:00<?, ?it/s]Loading pretrained parameter "encoder.encoder.0.cached_zero_vector". Loading pretrained parameter "encoder.encoder.0.W_i.weight".
    Loading pretrained parameter "encoder.encoder.0.W_h.weight".
    Loading pretrained parameter "encoder.encoder.0.W_o.weight".
    Loading pretrained parameter "encoder.encoder.0.W_o.bias".
    Loading pretrained parameter "readout.1.weight".
    Loading pretrained parameter "readout.1.bias"
    Loading pretrained parameter "readout.4.weight".
    Loading pretrained parameter "readout.4.bias".
    Moving model to cuda
      0%|
                      0/2 [00:00<?, ?it/s]
     50%|
                      1/2 [00:00<00:00, 2.27it/s]
    100%|
                    1/1 [00:00<00:00, 1.26it/s]Saving predictions to substances_preds.csv</p>
    Elapsed time = 0:00:01
fda_df = pd.read_csv("fda_approved.csv")
fda_df.head()
                zinc_id
                                                                      smiles
                                                                                Ħ
     0 ZINC000001530427
                                                 C[C@@H]10[C@@H]1P(=0)(O)O
     1 ZINC000003807804
                                           Clc1ccccc1C(c1ccccc1)(c1ccccc1)n1ccnc1
     2 ZINC000000120286
                                                Nc1nc(N)c2nc(-c3ccccc3)c(N)nc2n1
     3 ZINC000242548690 C[C@H]1O[C@@H](O[C@H]2[C@@H](O)C[C@H](O[C@H]3[...
     4 ZINC000000008492
                                                               Oc1ccc2cccnc12
```

```
View recommended plots
 Next steps:
arguments = [
    '--test_path', 'fda_approved.csv',
'--preds_path', 'fda_approved_preds.csv',
    '--checkpoint_dir', 'test_checkpoints_multimolecule', '--smiles_columns', 'smiles'
]
args = chemprop.args.PredictArgs().parse_args(arguments)
preds = chemprop.train.make_predictions(args=args)
     Loading training args
     Setting molecule featurization parameters to default.
     Loading data
     892it [00:00, 84347.53it/s]
                    ■| 892/892 [00:00<00:00, 63923.58it/s]Validating SMILES
     100%
     /usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557: UserWarning: This DataLoader will cre
       warnings.warn(_create_warning_msg(
     Test size = 892
                     | 0/1 [00:00<?, ?it/s]Loading pretrained parameter "encoder.encoder.o.cached zero_vector".
       0%1
     Loading pretrained parameter "encoder.encoder.0.W_i.weight".
     Loading pretrained parameter "encoder.encoder.0.W_h.weight".
     Loading pretrained parameter "encoder.encoder.0.W_o.weight".
     Loading pretrained parameter "encoder.encoder.0.W o.bias".
     Loading pretrained parameter "readout.1.weight".
     Loading pretrained parameter "readout.1.bias".
     Loading pretrained parameter "readout.4.weight".
Loading pretrained parameter "readout.4.bias".
     Moving model to cuda
                      | 0/18 [00:00<?, ?it/s]
                        1/18 [00:02<00:34,
       6%|
                                             2.05s/itl
      11% |
                       2/18 [00:02<00:15,
                                              1.03it/sl
      22%
                        4/18 [00:02<00:05, 2.46it/s]
      50%
                        9/18 [00:02<00:01, 6.87it/s]
                       12/18 [00:02<00:00, 9.41it/s]
1/1 [00:03<00:00, 3.30s/it]Saving predictions to fda_approved_preds.csv
      67%I
     100%|
     Elapsed time = 0:00:04
fda_preds_df = pd.read_csv("fda_approved_preds.csv")
fda_preds_df.head()
                 zinc_id
                                                               smiles HIV_active
                                                                                      扁
      0 ZINC000001530427
                                         C[C@@H]1O[C@@H]1P(=O)(O)O
                                                                           0.000114
      1 ZINC000003807804
                                   Clc1ccccc1C(c1ccccc1)(c1ccccc1)n1ccnc1
                                                                           0.021717
      2 ZINC000000120286
                                                                           0.020179
                                         Nc1nc(N)c2nc(-c3ccccc3)c(N)nc2n1
                            C[C@H]1O[C@@H](O[C@H]2[C@@H](O)C[C@H]
      3 ZINC000242548690
                                                                           0.021397
                                                           (O[C@H]3[...
      4 ZINC000000008492
                                                       Oc1ccc2cccnc12
                                                                           0.006810
             View recommended plots
 Next steps:
```

 $fda_preds_df['HIV_active_2'] = fda_preds_df['HIV_active'].apply(lambda x: 1 if x > 0.8 else 0)$

fda_preds_df = fda_preds_df[fda_preds_df['HIV_active'] != "Invalid SMILES"]

fda_preds_df['HIV_active'] = fda_preds_df['HIV_active'].astype(float)

fda_preds_df.describe()

fda_preds_df.head()

```
HIV_active
                                                           \blacksquare
            count 8.920000e+02
                           3.120089e-02
             mean
                            7.911301e-02
               std
                            2.711503e-08
              min
              25%
                            4.847819e-03
                            1.207062e-02
              50%
              75%
                           2.594892e-02
                           8.708455e-01
              max
                                     zinc_id
                                                                                                      smiles HIV_active HIV_active_2
                                                                C[C@@H]1O[C@@H]1P(=O)
            0 ZINC000001530427
                                                                                                                               0.000114
                                                                                                                                                                             0
                                                                                                            (O)O
                                                                           Clc1cccc1C(c1cccc1)
            1 ZINC000003807804
                                                                                                                               0.021717
                                                                                   (c1cccc1)n1ccnc1
                                                                                         Nc1nc(N)c2nc(-
            2 ZINC000000120286
                                                                                                                               0.020179
                                                                                                                                                                             0
                                                                                 c3cccc3)c(N)nc2n1
                                                                                 C[C@H]10[C@@H]
                                                                                             View recommended plots
   Next steps:
                             View recommended plots
# Filter rows where 'target_column' is equal to 1
fda_preds_df_filtered = fda_preds_df[fda_preds_df['HIV_active_2'] == 1]
fda_preds_df_filtered
                                         zinc_id
                                                                                                                        smiles HIV_active HIV_active_
                                                             O{=}c1[nH]cnc2c1ncn2[C@H]1CC[C@@H]\\
                      ZINC000013597823
                                                                                                                                                0.870845
                                                                                    Cc1cn([C@H]2C=C[C@@H]
            910 _ 7INICODODOD127994
   Next steps:
                              View recommended plots
smiles_to_check = fda_preds_df_filtered['smiles'].to_list()
print(f"smiles to check: {smiles_to_check}")
           smiles \ to \ check: \ ['0=c1[nH]cnc2c1ncn2[C@H]1CC[C@@H](C0)01', \ 'Cc1cn([C@H]2C=C[C@@H](C0)02)c(=0)[nH]c1=0'] \ (co1cn([C@H]2C=C[C@M](C0)02)c(=0)[nH]c1=0'] \ (co1cn([C@H]2C=C[C@M](C0)02)c(=0)[nH]c1=0'] \ (co1cn([C@M]2C=C[C@M](C0)02)c(=0)[nH]c1=0'] hiv_df_sampled_2[hiv_df_sampled_2['smiles'].isin(smiles_to_check)]
          NameError
                                                                                                            Traceback (most recent call last)
          <ipython-input-47-97b3985eab54> in <cell line: 1>()
                  -> 1 hiv_df_sampled_2[hiv_df_sampled_2['smiles'].isin(smiles_to_check)]
          NameError: name 'hiv_df_sampled_2' is not defined
hiv_df[hiv_df['smiles'].isin(smiles_to_check)]
                smiles activity HIV_active
bp_df[bp_df['smiles'].isin(smiles_to_check)]
                                                                          \blacksquare
                num name p_np smiles
fda_df[fda_df['smiles'].isin(smiles_to_check)]
                                         zinc_id
                                                                                                                                          smiles
                                                                                                                                                               \blacksquare
            321 ZINC000013597823
                                                                  O=c1[nH]cnc2c1ncn2[C@H]1CC[C@@H](CO)O1
            819 ZINC00000137884 Cc1cn([C@H]2C=C[C@@H](CO)O2)c(=O)[nH]c1=O
```

```
fda_df_final = pd.merge(fda_df[fda_df['smiles'].isin(smiles_to_check)], fda_preds_df_filtered, on='smiles' )
fda_df_final
```

```
zinc_id_y HIV_acti
                                                        smiles
               zinc id x
                           O=c1[nH]cnc2c1ncn2[C@H]1CC[C@@H]
      0 ZINC000013597823
                                                                ZINC000013597823
                                                                                      0.870
                                                        (CO)O1
                                      Cc1cn([C@H]2C=C[C@@H] 7INIC00000137994
      1 ZINICOOOOO127004
                                                                                      00111
 Next steps:
              View recommended plots
fda_df_final.to_csv('fda_approved_result.csv', index=False)
  # !wget https://zinc15.docking.org/substances/subsets/named.csv
     --2024-03-10 05:58:28-- <a href="https://zinc15.docking.org/substances/subsets/named.csv">https://zinc15.docking.org/substances/subsets/named.csv</a>
     Resolving zinc15.docking.org (zinc15.docking.org)... 169.230.75.4
     Connecting to zinc15.docking.org (zinc15.docking.org)|169.230.75.4|:443... connected.
     HTTP request sent, awaiting response... 200 OK
     Length: unspecified [text/csv]
     Saving to: 'named.csv.1'
     named.csv.1
                                                            9.28K --.-KB/s
                                                                                  in 0.04s
     2024-03-10 05:58:29 (242 KB/s) - 'named.csv.1' saved [9499]
zinc_df = pd.read_csv("named.csv")
zinc_df.head()
zinc_df.tail()
                                                                              smiles
                                                                                        \blacksquare
                  zinc id
      0 ZINC000030727788
                                C=C[C@]1(C)C[C@@H](OC(=O)CSC(C)(C)CNC(=O)[C@H]...
      1 ZINC000150377216 CCCCCC/C=C\C/C=C\CCCCCCC(=0)OC[C@H](COCCCCCC...
      2 ZINC000100780125
                               CC(=O)O[C@H]1C[C@](C)(O)[C@@H]2CC=C(C)[C@@H]2[...
       ZINC000006580536
                                                  O=C(O)[C@H](Cc1cccc1)N(CCCI)CCCI
      4 ZINC000150351802
                                   O = C1C[C@H](c2ccc(O)c(O)c2)Oc2c1c(O)cc(O[C@H]1O...
                      zinc_id
                                                                                        ıı.
                                C/C(=C\setminus CO)CC/C=C(\setminus C)CCC[C@@H](C)CCC[C@H](C)CCC...
      22959 ZINC000015253718
                                     CCCCCCCCCCCCCCCCCCC(C@@H](O)C[C@@H]
      22960 ZINC000043888360
                                                                           (O)CCCCC
      22961 ZINC000096006009
                                                     Cc1noc(NS(=O)(=O)c2ccc(N)cc2)c1C
                                        CC/C=C\C/C=C\C/C=C\CCCCCCC(=O)OC[C@@H]
      22962 ZINC000150375318
                                                                           (COC(=O...
arguments = [
    '--test_path', 'named.csv',
'--preds_path', 'named_preds.csv',
    '--checkpoint_dir', 'test_checkpoints_multimolecule', '--smiles_columns', 'smiles'
]
args = chemprop.args.PredictArgs().parse_args(arguments)
preds = chemprop.train.make_predictions(args=args)
```

```
J0J/U9Z [UZ:1J\U0:24,
                                          4.3/1L/5]
 00°
85%
                  587/692
                          [02:15<00:23.
                                          4.48it/sl
85%
                  589/692
                          [02:17<00:34,
                                          3.00it/s]
                  593/692
 86%
                          [02:17<00:20,
                                          4.92it/s]
 86%
                  595/692
                          [02:17<00:20,
                                          4.75it/s]
 86%
                  597/692
                          [02:18<00:25,
                                          3.68it/sl
87%
                  601/692
                          [02:18<00:15,
                                          5.85it/s]
 87%
                  603/692
                          [02:19<00:16,
                                          5.29it/s]
 87%
                  605/692
                          [02:20<00:22,
                                          3.92it/sl
88%
                  609/692
                          [02:20<00:13,
                                          6.19it/s]
 88%
                  611/692
                          [02:20<00:14,
                                          5.53it/s]
 89%
                  613/692
                          [02:21<00:19,
                                          4.00it/s]
89%1
                  617/692
                          [02:21<00:12,
                                          6.24it/sl
 89%
                  619/692
                          [02:22<00:12,
                                          5.82it/s]
 90%
                  621/692
                          [02:23<00:16,
                                          4.19it/s]
 90%
                  625/692
                          [02:23<00:10,
                                          6.47it/s]
                          [02:24<00:15,
 91%
                  627/692
                                          4.19it/sl
91%
                  629/692
                          [02:24<00:15,
                                          4.11it/s]
 92%
                  634/692
                          [02:24<00:08,
                                          7.02it/s]
 92%
                  636/692
                          [02:25<00:10,
                                          5.36it/s]
                          [02:27<00:16,
                  638/692
                                          3.19it/sl
 92%
 93%
                  641/692
                          [02:27<00:11,
                                          4.49it/s]
 93%
                  643/692
                          [02:27<00:12,
                                          4.03it/s]
 93%
                  645/692
                          [02:28<00:14.
                                          3.29it/sl
                          [02:28<00:09,
 94%
                  648/692
                                          4.79it/s]
 94%
                  651/692
                          [02:29<00:07,
                                          5.22it/s]
 94%|
                  653/692
                          [02:30<00:09,
                                          3.93it/s]
                          [02:30<00:05,
 95%1
                  657/692
                                          6.19it/sl
 95%
                  659/692
                          [02:31<00:08,
                                          4.07it/sl
 96%
                  661/692
                          [02:31<00:07,
                                          4.02it/s]
 96%
                  664/692
                          [02:32<00:04,
                                          5.65it/s]
                  666/692
 96%1
                          [02:32<00:03,
                                          6.72it/sl
 97%
                  668/692
                          [02:32<00:03,
                                          6.06it/s]
97%
                  670/692
                          [02:33<00:05,
                                          4.09it/s]
 97%|
                  673/692
                          [02:33<00:03,
                                          5.98it/s]
                          [02:34<00:03,
                  675/692
 98%
                                          5.19it/sl
 98%
                  677/692
                          [02:35<00:03.
                                          3.93it/sl
 99%
                          [02:35<00:01,
                  683/692
                                          7.59it/s]
 99%
                  685/692
                          [02:35<00:00,
                                          8.15it/s]
100%
                 691/692 [02:35<00:00,
                                         10.32it/s]
100%|
               || 1/1 [02:36<00:00, 156.28s/it]
Saving predictions to named_preds.csv
Flansed time = 0:02:50
```

zinc_preds_df = pd.read_csv("named_preds.csv")

```
        zinc_id
        smiles
        HIV_active

        0
        ZINC000030727788
        C=C[C@]1(C)C[C@@H](OC(=O)CSC(C) (C)CNC(=O)[C@H]...
        0.034702

        Next stepHNC0@) 5089/7246ommended plots

CCCCCC/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C\C/C=C
```

Filter rows where 'target_column' is equal to 1
zinc_preds_df_filtered = zinc_preds_df[zinc_preds_df['HIV_active_2'] == 1]
zinc_preds_df_filtered

		1 to 18 of 18 entries Filter 🚨 🔞					
index	zinc_id	smiles	HIV_active				
486	ZINC000000137884	Cc1cn([C@H]2C=C[C@@H](CO)O2)c(=O)[nH]c1=O	0.844088733196258				
664	ZINC000000039906	Nc1ccn([C@H]2CC[C@@H](CO)O2)c(=O)n1	0.87989950180053				
1673	ZINC000005551645	CC(C) = CCN1Cc2c(CI)ccc3[nH]c(=S)n(c23)C[C@@H]1C	0.857422471046447				
2491	ZINC000001611085	Nc1nc(=O)n([C@H]2CC[C@H](CO)O2)cc1F	0.890377223491668				
7718	ZINC000043313038	CCCCCCCCCCSC[C@@H](CO[P@@](=O) (O)OC[C@H]10[C@@H](n2cc(C)c(=O) [nH]c2=O)C[C@@H]1F)OCCCCCCCCC	0.83557295799255				
8880	ZINC000003809864	CCCc1cc(=O)oc2c3c(c4c(c12)OC(C)(C)CC4)O[C@@H] (C)[C@H](C)[C@@H]3O	0.843889176845550				
11356	ZINC000016952419	Nc1nc(=O)n([C@H]2CC[C@@H](CO)O2)cc1F	0.894337236881256				
13087	ZINC000032016993	Nc1ccn([C@@H]2CC[C@H](CO[P@@](=O)(O)O[P@] (=O)(O)OP(=O)(O)O)O2)c(=O)n1	0.86944174766540				
15124	ZINC000015042997	CC[C@H]1CC[C@@H](CC)O1	0.8721865415573				
15334	ZINC000013516800	Nc1ccn([C@H]2CC[C@@H](CO[P@@](=O) (O)O[P@@](=O)(O)OP(=O)(O)O)O2)c(=O)n1	0.86774849891662				
16695	ZINC000003870291	CCCc1cc(=O)oc2c3c(c4c(c12)OC(C) (C)C=C4)O[C@@H](C)[C@@H](C)[C@@H]3O	0.8273838162422				
17320	ZINC000012503817	Cc1cn([C@H]2C[C@H](N=[N+]=[N-])[C@@H](COP(=O) (O)O)O2)c(=O)[nH]c1=O	0.91335463523864				
20161	ZINC000012502287	Cc1cn([C@H]2C=C[C@@H](CO[P@](=O)(O)OP(=O) (O)O)O2)c(=O)[nH]c1=O	0.87298274040222				
24565	ZINC000034932069	Cc1cn([C@H]2C[C@@H](N=[N+]=[N-])[C@H] (CO[P@@](=O)(O)OP(=O)(O)O)O2)c(=O)[nH]c1=O	0.904866278171539				
25932	ZINC000017175432	Nc1nc(=O)n([C@@H]2CC[C@@H](CO)O2)cc1F	0.89636123180389				
26697	ZINC000027871222	CC(=0)N[C@@H](Cc1ccc(O[P@](=0) (O)OC[C@H]2O[C@@H](n3cc(C)c(=0)	0.841066479682922				

Next steps:

View recommended plots

zinc_preds_df_filtered.to_csv('zinc_final_result.csv', index=False)

from google.colab import drive
drive.mount('/content/drive')

Mounted at /content/drive

!mkdir '/content/drive/My Drive/Chemprop_Backup_HIV_ALL_DATA/'

!pwd

/content

!ls -al

```
total 9612

drwxr-xr-x 1 root root

drwxr-xr-x 1 root root

-rw-r--r-- 1 root root

4096 Mar 11 07:15 .

4096 Mar 11 05:35 ..

4096 Mar 11 07:04 BBBP 2.csv
```