results

May 10, 2024

1 Results

[ ]:
```
import os
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as stats
import sys

sys.path.insert(1, "/Users/simon/Documents/II/Dissertation/")
from src.evaluate import get_results_df

%load_ext autoreload
%autoreload 2
```

Collect results

[ ]:
```
models = ["Linear", "ARIMA", "RandomForest", "CNN", "LSTM", "ConvLSTM"]
stocks = ["NVDA", "JPM", "HD", "UNH"]

dfs = []
for m in models:
    for s in stocks:
        dfs.append(get_results_df(f"{m}_{s}"))
dfs = pd.concat(dfs)
dfs.to_csv("./results.csv")
```

```
Loading Linear_NVDA.
Rank 1: trial no. 0, value: 45.0199203187251. Run completed at 2024-04-29
16:52:25.570862
Loading Linear_JPM.
Rank 1: trial no. 0, value: 46.613545816733065. Run completed at 2024-04-29
16:52:27.015066
Loading Linear_HD.
Rank 1: trial no. 0, value: 52.589641434262944. Run completed at 2024-04-29
16:52:28.379346
Loading Linear_UNH.
```

```
Rank 1: trial no. 0, value: 47.808764940239044. Run completed at 2024-04-29
16:52:29.689755
Loading ARIMA_NVDA.
Rank 1: trial no. 18, value: 56.97211155378486. Run completed at 2024-04-29
17:11:04.256046
Loading ARIMA_JPM.
Rank 1: trial no. 1, value: 52.98804780876494. Run completed at 2024-04-29
17:15:08.552541
Loading ARIMA_HD.
Rank 1: trial no. 4, value: 52.98804780876494. Run completed at 2024-04-29
17:27:20.232495
Loading ARIMA_UNH.
Rank 1: trial no. 1, value: 47.01195219123506. Run completed at 2024-04-29
17:35:18.839560
Loading RandomForest_NVDA.
Rank 1: trial no. 1, value: 50.59760956175299. Run completed at 2024-04-29
17:44:32.475530
Loading RandomForest_JPM.
Rank 1: trial no. 8, value: 53.38645418326693. Run completed at 2024-04-29
17:51:43.110122
Loading RandomForest_HD.
Rank 1: trial no. 6, value: 54.18326693227091. Run completed at 2024-04-29
17:56:56.054294
Loading RandomForest_UNH.
Rank 1: trial no. 3, value: 55.77689243027888. Run completed at 2024-04-29
17:59:37.088842
Loading CNN_NVDA.
Rank 1: trial no. 11, value: 0.5737051963806152. Run completed at 2024-04-29
20:22:15.814904
Loading CNN_JPM.
Rank 1: trial no. 9, value: 0.5737051963806152. Run completed at 2024-04-29
18:34:47.643948
Loading CNN_HD.
Rank 1: trial no. 0, value: 0.5498008131980896. Run completed at 2024-04-29
18:35:17.552823
Loading CNN_UNH.
Rank 1: trial no. 8, value: 0.5816733241081238. Run completed at 2024-04-29
18:44:16.965952
Loading LSTM_NVDA.
Rank 1: trial no. 0, value: 0.5537848472595215. Run completed at 2024-04-29
18:01:30.993116
Loading LSTM_JPM.
Rank 1: trial no. 3, value: 0.6175298690795898. Run completed at 2024-04-29
18:13:38.976207
Loading LSTM_HD.
Rank 1: trial no. 4, value: 0.6055777072906494. Run completed at 2024-04-29
18:19:41.955427
Loading LSTM_UNH.
```

```
Rank 1: trial no. 11, value: 0.5896414518356323. Run completed at 2024-04-29
20:23:47.878337
Loading ConvLSTM_NVDA.
Rank 1: trial no. 2, value: 0.518652081489563. Run completed at 2024-04-29
18:47:06.218729
Loading ConvLSTM_JPM.
Rank 1: trial no. 26, value: 0.5697211027145386. Run completed at 2024-04-29
20:35:01.199259
Loading ConvLSTM_HD.
Rank 1: trial no. 6, value: 0.5231999158859253. Run completed at 2024-04-29
19:04:03.502803
Loading ConvLSTM_UNH.
Rank 1: trial no. 0, value: 0.5577689409255981. Run completed at 2024-04-29
16:26:05.723444
```

Load results if already exists

[ ]:
```
path = "./results.csv"
if os.path.exists(path):
    dfs = pd.read_csv(path, header=[0, 1], index_col=0)
dfs["Model Type"] = dfs.index.str.split("_").str[0]
dfs["Stock"] = dfs.index.str.split("_").str[1]
```

Aggregating by stock

[ ]:
```
df = dfs.copy()
df.drop(columns=["Hyperparameters", "Model Type"]).groupby("Stock").mean().loc[
    ["NVDA", "JPM", "HD", "UNH"]
]
```

```
/var/folders/d7/ktx3dym91yjgj_gpmnfs0rh00000gn/T/ipykernel_22281/248852036.py:2:
PerformanceWarning: dropping on a non-lexsorted multi-index without a level
parameter may impact performance.
  df.drop(columns=["Hyperparameters", "Model
Type"]).groupby("Stock").mean().loc[["NVDA", "JPM", "HD", "UNH"]]
```

[ ]:
```
      Validation set                                                        \
                  R2         MSE        RMSE         MAE           p    Accuracy
Stock
NVDA     -0.24753428 0.00196531 0.04376697 0.03503818 0.03884602 49.53519256
JPM      -0.26228733 0.00044194 0.02081327 0.01618928 0.02068996 48.80478088
HD       -0.13828215 0.00044386 0.02092433 0.01598344 0.07250368 51.92563081
UNH      -0.17845246 0.00027840 0.01650261 0.01281574 0.03330397 51.99203187

                                                             Test set  \
      Avg. daily return Std. daily return Risk adj. return          R2
Stock
NVDA        -0.00210417        0.03325528      -0.06049100 -0.25203186
```

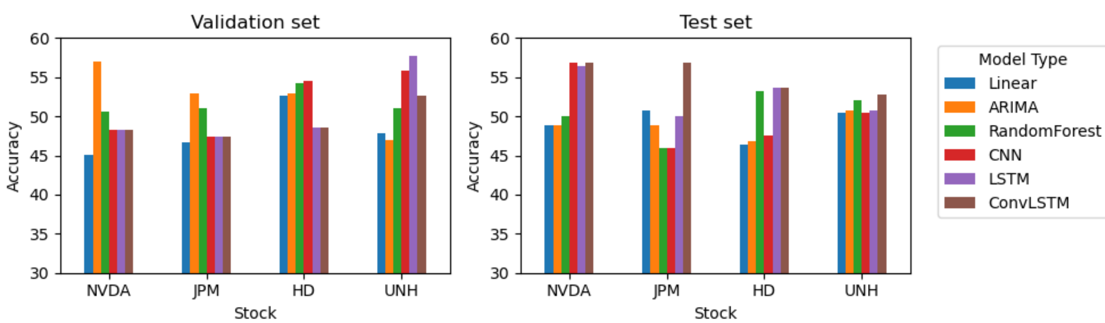
```
JPM         -0.00034623        0.01426815      -0.02285721 -0.29839481
HD          -0.00023387        0.01587887      -0.01208317 -0.16416481
UNH          0.00002149        0.01246166      -0.00020706 -0.15088191

                                                                \
             MSE       RMSE        MAE           p    Accuracy
Stock
NVDA  0.00108453 0.03257765 0.02361088 -0.00395278 52.93333333
JPM   0.00022075 0.01467125 0.01074293 -0.03470588 49.73333333
HD    0.00021324 0.01449804 0.01078709  0.01850120 50.20000000
UNH   0.00020444 0.01417508 0.00998843  0.03085183 51.20000000


      Avg. daily return Std. daily return Risk adj. return
Stock
NVDA         0.00344616        0.02520458       0.13110339
JPM          0.00054191        0.01030267       0.05189790
HD           0.00023232        0.01007062       0.02157074
UNH          0.00015475        0.00913768       0.01866290
```

[ ]:
```python
# Plotting
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(10, 3))

for i, set in enumerate(["Validation set", "Test set"]):
    df = dfs.copy()
    df = df.pivot(index="Stock", columns="Model Type", values=(set, "Accuracy"))
    df = df.loc[["NVDA", "JPM", "HD", "UNH"]]  # Re-order rows
    df = df[
        ["Linear", "ARIMA", "RandomForest", "CNN", "LSTM", "ConvLSTM"]
    ]  # Re-order columns
    display(df)
    df.plot(kind="bar", ax=axs[i])
    axs[i].set_title(f"{set}")
    axs[i].set_ylabel("Accuracy")
    axs[i].set_xlabel("Stock")
    axs[i].tick_params(labelrotation=0)
    axs[i].get_legend().remove()
    axs[i].set_ylim([30, 60])


axs[1].legend(title="Model Type", bbox_to_anchor=(1.05, 1), loc="upper left")
fig.tight_layout()
plt.show()
```

```
Model Type      Linear       ARIMA  RandomForest          CNN        LSTM  \
Stock
NVDA       45.01992032 56.97211155   50.59760956 48.20717131 48.20717131
```

```
JPM         46.61354582 52.98804781   50.99601594 47.41035857 47.41035857
HD          52.58964143 52.98804781   54.18326693 54.58167331 48.60557769
UNH         47.80876494 47.01195219   50.99601594 55.77689243 57.76892430

Model Type    ConvLSTM
Stock
NVDA        48.20717131
JPM         47.41035857
HD          48.60557769
UNH         52.58964143
```

```
Model Type       Linear       ARIMA  RandomForest         CNN        LSTM  \
Stock
NVDA        48.80000000 48.80000000   50.00000000 56.80000000 56.40000000
JPM         50.80000000 48.80000000   46.00000000 46.00000000 50.00000000
HD          46.40000000 46.80000000   53.20000000 47.60000000 53.60000000
UNH         50.40000000 50.80000000   52.00000000 50.40000000 50.80000000

Model Type    ConvLSTM
Stock
NVDA        56.80000000
JPM         56.80000000
HD          53.60000000
UNH         52.80000000
```



First, we observe how each model performs on each stock. In terms of accuracy, there is no clear highest-performing model on the validation set. On the other hand, the test set shows the ConvLSTM model outperforming other model types on all stocks.

[ ]:
```
# Aggregate by Model Type
df = dfs.copy()
df.drop(columns=["Hyperparameters", "Stock"]).groupby("Model Type").mean().loc[
    ["Linear", "ARIMA", "RandomForest", "CNN", "LSTM", "ConvLSTM"]
]
```

```
/var/folders/d7/ktx3dym91yjgj_gpmnfs0rh00000gn/T/ipykernel_22281/445887624.py:3:
```

```
PerformanceWarning: dropping on a non-lexsorted multi-index without a level
parameter may impact performance.
  df.drop(columns=["Hyperparameters", "Stock"]).groupby("Model
Type").mean().loc[["Linear", "ARIMA", "RandomForest", "CNN", "LSTM",
"ConvLSTM"]]
```

[ ]:

	Validation set				
	R2	MSE	RMSE	MAE	p
Model Type					
Linear	-0.02066762	0.00065106	0.02361975	0.01858800	0.00687075
ARIMA	-1.02644547	0.00135590	0.03361967	0.02663852	0.03078746
RandomForest	-0.03631573	0.00068872	0.02402783	0.01888253	0.06086197
CNN	-0.12797410	0.00068466	0.02448429	0.01912300	0.00949959
LSTM	-0.00628597	0.00064480	0.02347886	0.01832636	0.07087916
ConvLSTM	-0.02214544	0.00066911	0.02378037	0.01848158	0.06177991

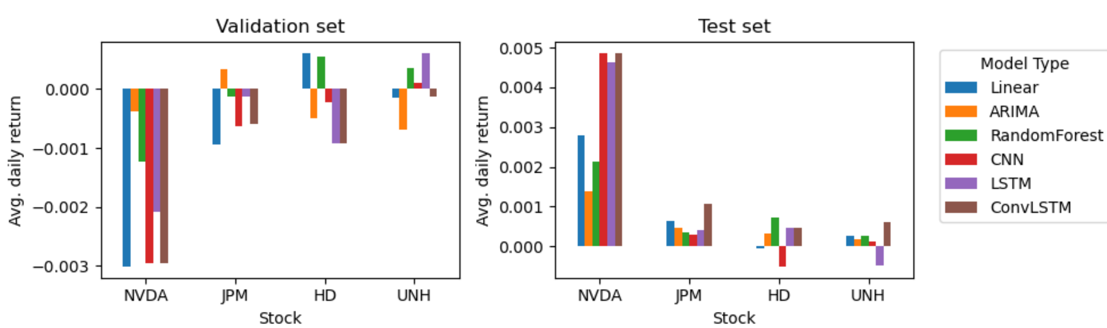
	Accuracy	Avg. daily return	Std. daily return	Risk adj. return
Model Type				
Linear	48.00796813	-0.00087223	0.01850491	-0.03379087
ARIMA	52.49003984	-0.00030584	0.01509480	-0.02210786
RandomForest	51.69322709	-0.00010573	0.01629282	0.00525725
CNN	51.49402390	-0.00092618	0.01982590	-0.03456280
LSTM	50.49800797	-0.00063349	0.02131060	-0.01753170
ConvLSTM	49.20318725	-0.00115072	0.02276692	-0.04072167

	Test set				
	R2	MSE	RMSE	MAE	p
Model Type					
Linear	-0.01909141	0.00035809	0.01752181	0.01252915	0.02385229
ARIMA	-1.01053333	0.00071815	0.02469201	0.01912823	-0.00055633
RandomForest	-0.10110938	0.00042627	0.01860393	0.01317114	-0.00732916
CNN	-0.16178257	0.00038139	0.01834945	0.01319566	-0.04282749
LSTM	-0.00462845	0.00035063	0.01737026	0.01233547	0.02478478
ConvLSTM	-0.00106495	0.00034991	0.01734557	0.01233434	0.00839879

	Accuracy	Avg. daily return	Std. daily return	Risk adj. return
Model Type				
Linear	49.10000000	0.00090831	0.01171694	0.05495246
ARIMA	48.80000000	0.00058564	0.01129133	0.04494016
RandomForest	50.30000000	0.00086942	0.01082230	0.07098626
CNN	50.20000000	0.00119086	0.01503570	0.03647862
LSTM	52.70000000	0.00125459	0.01608904	0.04510046
ConvLSTM	55.00000000	0.00175389	0.01711801	0.08239443

Looking at the mean accuracies of each model for the test set, we observe that the hybrid ConvLSTM is improved across all metrics over its CNN and LSTM predecessors. The second-best model is the LSTM model, followed by the CNN and Random Forest models. The ConvLSTM model, relative to the other models performs much better. Now turning our attention to the standard deviation of daily return, we observe that the statistical models all similarly have lower variation than the deep learning models. This suggests the trading decisions derived from the deep learning models result in riskier portfolios, whose values vary more than those of the statistical models. However, this is counter-balanced by the average daily return being higher for the deep learning models. Consequently, all models have similar risk adjusted returns, except the ConvLSTM model which is notably higher. Similar rankings can be observed from the traditional machine learning metrics, with higher accuracy correlating to higher average daily return, but as noted in Section X, this is not always true.

[ ]:
```python
# Plotting
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=(10, 3))

for i, set in enumerate(["Validation set", "Test set"]):
    df = dfs.copy()
    df = df.pivot(
        index="Stock", columns="Model Type", values=(set, "Avg. daily return")
    )
    df = df.loc[["NVDA", "JPM", "HD", "UNH"]]  # Re-order rows
    df = df[
        ["Linear", "ARIMA", "RandomForest", "CNN", "LSTM", "ConvLSTM"]
    ]  # Re-order columns
    df.plot(kind="bar", ax=axs[i])
    axs[i].set_title(f"{set}")
    axs[i].set_ylabel("Avg. daily return")
    axs[i].set_xlabel("Stock")
    axs[i].tick_params(labelrotation=0)
    axs[i].get_legend().remove()


axs[1].legend(title="Model Type", bbox_to_anchor=(1.05, 1), loc="upper left")
fig.tight_layout()
plt.show()
```



Viewing the average daily return for each of the models across the selected stocks shows large variation in NVIDIA stock. This can be explained with the high volatility of the stock during the validation and test set periods (2023 and 2024, respectively), where many external factors and events influenced sharp jumps in price, as can be seen in Figure X.

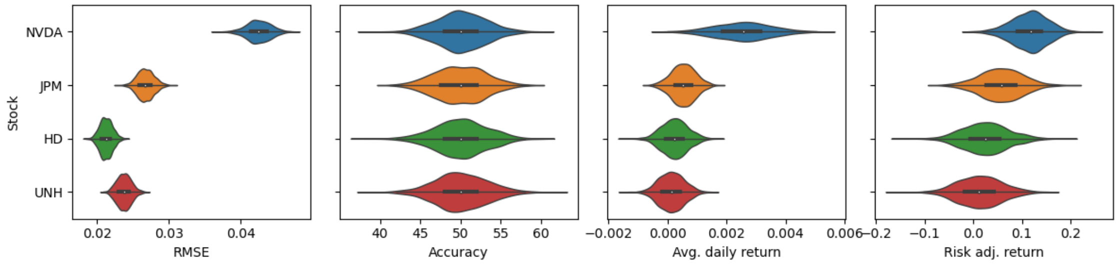
In summary, comparing the models to each other, we conclude that ConvLSTM model is the best, whereas the linear regression and ARIMA models are the worst. Now we shift our attention to comparing the models to a baseline random walk model.

[ ]:
```python
import seaborn as sns
from src.evaluate import random_walk

stocks = ["NVDA", "JPM", "HD", "UNH"]

random_df = []
for s in stocks:
    random_df.append(random_walk(s))
random_df = pd.concat(random_df)
random_df
```

[ ]:
```
              R2        MSE       RMSE        MAE           p   Accuracy  \
0   -1.05775320 0.00178245 0.04221912 0.03158757 -0.01961993 50.00000000
1   -1.08001233 0.00180174 0.04244685 0.03182528  0.00067114 49.60000000
2   -0.95982756 0.00169763 0.04120230 0.03102806  0.06319344 53.60000000
3   -0.93820740 0.00167890 0.04097440 0.03150312  0.02393293 48.40000000
4   -0.85960718 0.00161082 0.04013499 0.03134208  0.12671680 53.20000000
..          …          …          …          …           …          …
995 -1.87922097 0.00051145 0.02261517 0.01745124 -0.03715600 52.80000000
996 -1.87011769 0.00050983 0.02257939 0.01814187  0.14378865 55.20000000
997 -2.25343121 0.00057792 0.02403992 0.01892841 -0.03550563 50.40000000
998 -1.73058412 0.00048504 0.02202369 0.01778347  0.07138073 48.40000000
999 -2.14836870 0.00055926 0.02364858 0.01857498 -0.05694255 46.40000000

     Avg. daily return  Std. daily return  Risk adj. return Stock
0           0.00259022         0.02522597        0.10268063  NVDA
1           0.00243437         0.02148658        0.11329744  NVDA
2           0.00316054         0.01762301        0.17934184  NVDA
3           0.00350995         0.02116178        0.16586284  NVDA
4           0.00413856         0.02482279        0.16672422  NVDA
..                 …                  …                 …   …
995         0.00010428         0.00993493        0.01049597   UNH
996         0.00093807         0.00932627        0.10058320   UNH
997         0.00012910         0.00897467        0.01438475   UNH
998         0.00031571         0.00986056        0.03201728   UNH
999        -0.00011882         0.00851556       -0.01395273   UNH

[4000 rows x 10 columns]
```

[ ]:
```
df = random_df
display(df)
fig, axs = plt.subplots(nrows=1, ncols=4, sharey=True, figsize=(12, 3))
sns.violinplot(data=df, x="RMSE", y="Stock", ax=axs[0], linewidth=1)
sns.violinplot(data=df, x="Accuracy", y="Stock", ax=axs[1], linewidth=1).set(
    ylabel=None
)
sns.violinplot(data=df, x="Avg. daily return", y="Stock", ax=axs[2],␣
 ↪linewidth=1).set(
    ylabel=None
)
sns.violinplot(data=df, x="Risk adj. return", y="Stock", ax=axs[3],␣
 ↪linewidth=1).set(
    ylabel=None
)
fig.tight_layout()
```

```
             R2        MSE       RMSE        MAE           p   Accuracy  \
0   -1.05775320 0.00178245 0.04221912 0.03158757 -0.01961993 50.00000000
1   -1.08001233 0.00180174 0.04244685 0.03182528  0.00067114 49.60000000
2   -0.95982756 0.00169763 0.04120230 0.03102806  0.06319344 53.60000000
3   -0.93820740 0.00167890 0.04097440 0.03150312  0.02393293 48.40000000
4   -0.85960718 0.00161082 0.04013499 0.03134208  0.12671680 53.20000000
..          …          …          …          …           …           …
995 -1.87922097 0.00051145 0.02261517 0.01745124 -0.03715600 52.80000000
996 -1.87011769 0.00050983 0.02257939 0.01814187  0.14378865 55.20000000
997 -2.25343121 0.00057792 0.02403992 0.01892841 -0.03550563 50.40000000
998 -1.73058412 0.00048504 0.02202369 0.01778347  0.07138073 48.40000000
999 -2.14836870 0.00055926 0.02364858 0.01857498 -0.05694255 46.40000000

     Avg. daily return  Std. daily return  Risk adj. return Stock
0           0.00259022         0.02522597        0.10268063  NVDA
1           0.00243437         0.02148658        0.11329744  NVDA
2           0.00316054         0.01762301        0.17934184  NVDA
3           0.00350995         0.02116178        0.16586284  NVDA
4           0.00413856         0.02482279        0.16672422  NVDA
..                   …                  …                 …   …
995         0.00010428         0.00993493        0.01049597   UNH
996         0.00093807         0.00932627        0.10058320   UNH
997         0.00012910         0.00897467        0.01438475   UNH
998         0.00031571         0.00986056        0.03201728   UNH
999        -0.00011882         0.00851556       -0.01395273   UNH

[4000 rows x 10 columns]
```



[ ]:
```
random_df.groupby("Stock").mean()
```

[ ]:
```
              R2         MSE        RMSE         MAE           p    Accuracy  \
Stock
HD    -1.46025088 0.00045065 0.02120991 0.01665570 -0.00154551 50.02640000
JPM   -3.20422480 0.00071479 0.02671067 0.02112854 -0.00347414 49.91320000
NVDA  -1.08580890 0.00180676 0.04247356 0.03254093  0.00374187 50.04440000
UNH   -2.17078680 0.00056324 0.02371141 0.01861061  0.00136204 50.04960000

       Avg. daily return  Std. daily return  Risk adj. return
Stock
HD            0.00023891         0.00968711        0.02529536
JPM           0.00053071         0.00925316        0.05734307
NVDA          0.00254700         0.02185612        0.11533465
UNH           0.00013011         0.00954605        0.01351766
```

We can see the evaluation metric distributions of the random walk model across the selected stocks. Notably, the RMSE for a random walk model is much higher for NVIDIA, which reflects the high price volatility and unpredictability. However, this also meant a higher return during the test period of NVIDIA stock price. The accuracies have a mean of 50 may initially seem like a discrepancy as daily returns differ, but this is simply due to the compounding nature of stock returns.

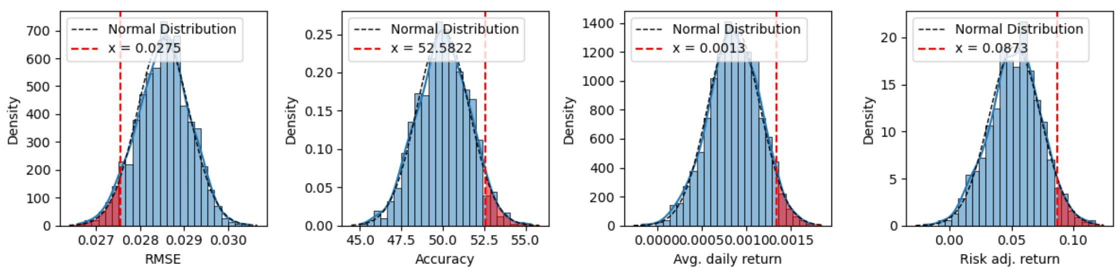
[ ]:
```
df = random_df.drop(columns=["Stock"]).groupby(random_df.index).mean()
display(df)

fig, axs = plt.subplots(nrows=1, ncols=4, figsize=(12, 3))
for i, metric in enumerate(
    ["RMSE", "Accuracy", "Avg. daily return", "Risk adj. return"]
):
    sns.histplot(df, x=metric, kde=True, ax=axs[i], stat="density")
    xmin, xmax = axs[i].get_xlim()
    x = np.linspace(xmin, xmax, 100)

    mean = df[metric].mean()
    std = df[metric].std()
    p = stats.norm.pdf(x, mean, std)
```

```
    axs[i].plot(x, p, "k", linewidth=1, label="Normal Distribution",␣
 ↪linestyle="dashed")

    if metric == "RMSE":
        ci = stats.norm.ppf(0.05, mean, std)
        axs[i].fill_between(x, p, where=(x <= ci), color="red", alpha=0.5)
    else:
        ci = stats.norm.ppf(0.95, mean, std)
        axs[i].fill_between(x, p, where=(x >= ci), color="red", alpha=0.5)
    axs[i].axvline(ci, color="red", linestyle="--", label=f"x = {ci:.4f}")
    axs[i].legend(loc="upper left")

fig.tight_layout()
```

```
             R2        MSE       RMSE        MAE          p    Accuracy  \
0   -1.95546575 0.00087338 0.02828586 0.02198506  0.03776665 50.20000000
1   -2.10949358 0.00090515 0.02895658 0.02238151 -0.02755672 50.20000000
2   -1.89863779 0.00084762 0.02801149 0.02169403  0.04287293 53.70000000
3   -1.99163340 0.00086011 0.02832100 0.02233371 -0.02568557 48.50000000
4   -1.95365457 0.00083973 0.02802742 0.02206717  0.03585953 52.00000000
..          …          …          …          …          …          …
995 -2.06676229 0.00091894 0.02894076 0.02224064 -0.03988918 49.10000000
996 -1.95490660 0.00091105 0.02877105 0.02234196  0.00612882 49.40000000
997 -2.08609802 0.00089164 0.02877677 0.02272362  0.01443309 49.70000000
998 -1.87897104 0.00088667 0.02838867 0.02225543  0.00235307 48.70000000
999 -2.07871308 0.00092113 0.02905704 0.02281539 -0.02309645 48.30000000

     Avg. daily return  Std. daily return  Risk adj. return
0           0.00110122         0.01366336        0.07209553
1           0.00079224         0.01182458        0.04968050
2           0.00127771         0.01142796        0.10029224
3           0.00093262         0.01240810        0.04620775
4           0.00133348         0.01324890        0.07560883
..                 …                  …                 …
995         0.00075601         0.01311611        0.03696599
996         0.00087363         0.01305440        0.05726713
997         0.00105711         0.01168628        0.07901336
998         0.00079473         0.01331819        0.02982082
999         0.00040858         0.01092924        0.02214841

[1000 rows x 9 columns]
```

```
/Users/simon/anaconda3/envs/proj/lib/python3.9/site-
packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/Users/simon/anaconda3/envs/proj/lib/python3.9/site-
```

```
packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/Users/simon/anaconda3/envs/proj/lib/python3.9/site-
packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/Users/simon/anaconda3/envs/proj/lib/python3.9/site-
packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



[ ]:
```python
df = dfs.copy()
df.drop(columns=["Hyperparameters", "Stock"]).groupby("Model Type").mean().loc[
    ["Linear", "ARIMA", "RandomForest", "CNN", "LSTM", "ConvLSTM"]
]["Test set"]
```

```
/var/folders/d7/ktx3dym91yjgj_gpmnfs0rh00000gn/T/ipykernel_58740/377110121.py:2:
PerformanceWarning: dropping on a non-lexsorted multi-index without a level
parameter may impact performance.
  df.drop(columns=["Hyperparameters", "Stock"]).groupby("Model
Type").mean().loc[["Linear", "ARIMA", "RandomForest", "CNN", "LSTM",
"ConvLSTM"]]["Test set"]
```

[ ]:
```
                     R2         MSE        RMSE         MAE           p  \
Model Type
Linear       -0.01909141 0.00035809 0.01752181 0.01252915  0.02385229
ARIMA        -1.01053333 0.00071815 0.02469201 0.01912823 -0.00055633
RandomForest -0.10110938 0.00042627 0.01860393 0.01317114 -0.00732916
CNN          -0.16178257 0.00038139 0.01834945 0.01319566 -0.04282749
LSTM         -0.00462845 0.00035063 0.01737026 0.01233547  0.02478478
ConvLSTM     -0.00106495 0.00034991 0.01734557 0.01233434  0.00839879

                 Accuracy  Avg. daily return  Std. daily return  \
```

```
Model Type
Linear       49.10000000         0.00090831          0.01171694
ARIMA        48.80000000         0.00058564          0.01129133
RandomForest 50.30000000         0.00086942          0.01082230
CNN          50.20000000         0.00119086          0.01503570
LSTM         52.70000000         0.00125459          0.01608904
ConvLSTM     55.00000000         0.00175389          0.01711801

              Risk adj. return
Model Type
Linear              0.05495246
ARIMA               0.04494016
RandomForest        0.07098626
CNN                 0.03647862
LSTM                0.04510046
ConvLSTM            0.08239443
```

Performing the statistical tests, we see that only the ConvLSTM model is statistically better than the random walk model in terms of RMSE, accuracy and average daily return. However, the ConvLSTM model does not fall in the critical region for risk adjusted return. This suggests that although the ConvLSTM is able to generate higher returns, it comes with more risk. No other models are statistically significant across average daily return, although the LSTM model also outperforms the random walk model in terms of accuracy. Finally, all models have an improved RMSE, which supports the use of financial metrics, demonstrating that a good RMSE does not always translate to good trading performance.

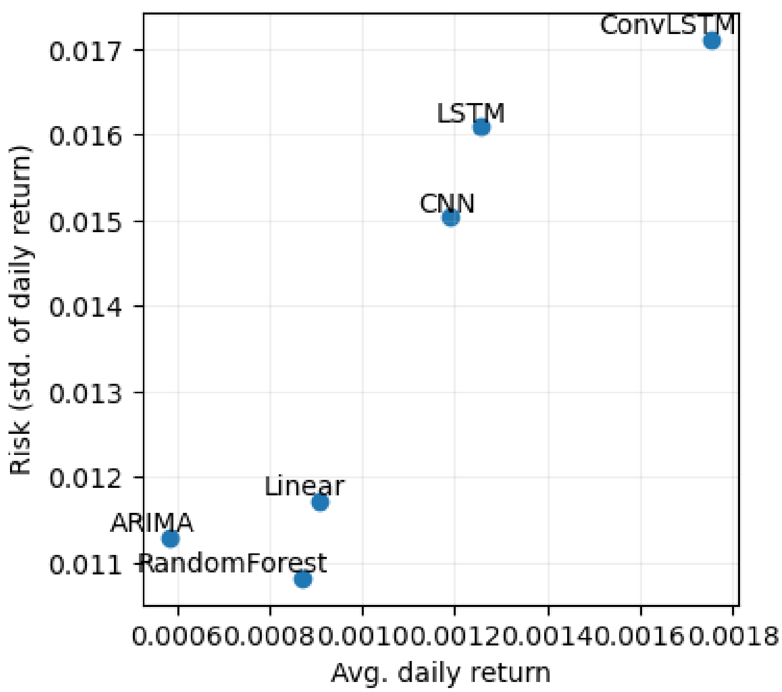
1.1 Risk analysis

[ ]:
```
df = dfs.copy()
df = (
    df.drop(columns=["Stock", "Hyperparameters"])
    .groupby("Model Type")
    .mean()["Test set"]
)
display(df[["Avg. daily return", "Std. daily return"]])

fig, ax = plt.subplots(figsize=(4, 4))
ax.scatter(x=df["Avg. daily return"], y=df["Std. daily return"])
plt.xlabel("Avg. daily return")
plt.ylabel("Risk (std. of daily return)")
ax.grid(True, alpha=0.2)

for label, x, y in zip(df.index, df["Avg. daily return"], df["Std. daily␣
 ↪return"]):
    plt.annotate(
        label,
        xy=(x, y),
```

```
        xytext=(10, 0),
        textcoords="offset points",
        ha="right",
        va="bottom",
    )
```

```
/var/folders/d7/ktx3dym91yjgj_gpmnfs0rh00000gn/T/ipykernel_22281/2130644621.py:2
: PerformanceWarning: dropping on a non-lexsorted multi-index without a level
parameter may impact performance.
  df = df.drop(columns=["Stock", "Hyperparameters"]).groupby("Model
Type").mean()["Test set"]
```

```
              Avg. daily return  Std. daily return
Model Type
ARIMA                0.00058564         0.01129133
CNN                  0.00119086         0.01503570
ConvLSTM             0.00175389         0.01711801
LSTM                 0.00125459         0.01608904
Linear               0.00090831         0.01171694
RandomForest         0.00086942         0.01082230
```

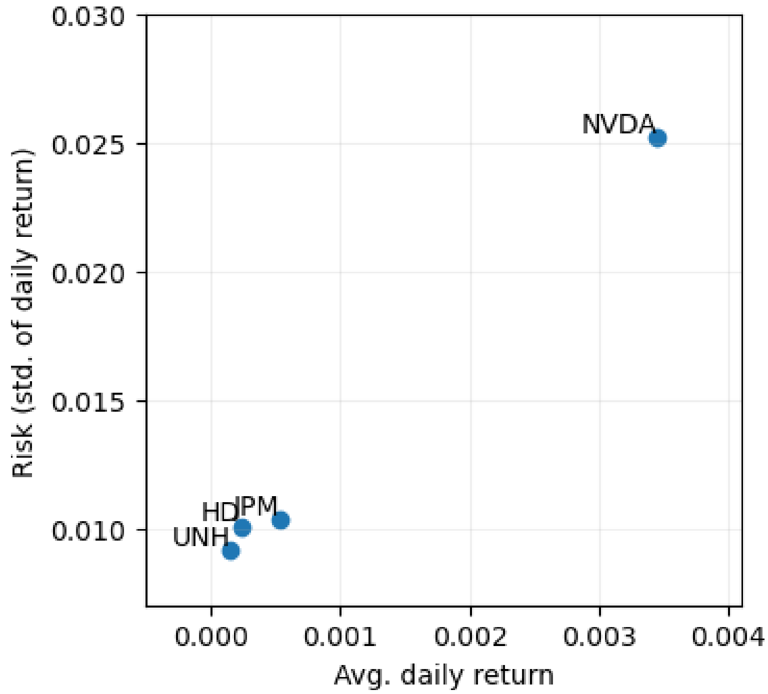



```
[ ]: df = dfs.copy()
     df = (
         df.drop(columns=["Model Type", "Hyperparameters"])
         .groupby("Stock")
```

```
    .mean()["Test set"]
)
display(df[["Avg. daily return", "Std. daily return"]])

fig, ax = plt.subplots(figsize=(4, 4))
ax.scatter(x=df["Avg. daily return"], y=df["Std. daily return"])
plt.xlabel("Avg. daily return")
plt.ylabel("Risk (std. of daily return)")
ax.grid(True, alpha=0.2)
ax.set_ylim((0.007, 0.03))
ax.set_xlim((-0.0005, 0.0041))

for label, x, y in zip(df.index, df["Avg. daily return"], df["Std. daily␣
 ↪return"]):
    plt.annotate(
        label,
        xy=(x, y),
        xytext=(0, 0),
        textcoords="offset points",
        ha="right",
        va="bottom",
    )
```

```
/var/folders/d7/ktx3dym91yjgj_gpmnfs0rh00000gn/T/ipykernel_22281/1779348945.py:2
: PerformanceWarning: dropping on a non-lexsorted multi-index without a level
parameter may impact performance.
  df = df.drop(columns=["Model Type",
"Hyperparameters"]).groupby("Stock").mean()["Test set"]
```

	Avg. daily return	Std. daily return
Stock		
HD	0.00023232	0.01007062
JPM	0.00054191	0.01030267
NVDA	0.00344616	0.02520458
UNH	0.00015475	0.00913768


0.030
0.025
0.020
0.015
0.010
Risk (std. of daily return)
NVDA
HD
JPM
UNH
0.000
0.001
0.002
0.003
0.004
Avg. daily return