adversarial_attack

January 16, 2025

[28]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPClassifier
from sklearn.decomposition import PCA


%matplotlib inline
```

[29]:
```
path = 'data/swat_newdataset/SWaT.A3_dataset_Jul 19_labelled.xlsx'

df = pd.read_excel(path, skiprows=[0, 2])
df
```

[29]:
```
                          GMT +0  Attack  Label   FIT 101     LIT 101  \
0           2019-07-20T04:30:00Z  benign      0  0.000000  729.865800
1           2019-07-20T04:30:01Z  benign      0  0.000000  729.434000
2     2019-07-20T04:30:02.004013Z  benign      0  0.000000  729.120000
3     2019-07-20T04:30:03.004013Z  benign      0  0.000000  728.688200
4           2019-07-20T04:30:04Z  benign      0  0.000000  727.706900
…                            …     …    …       …         …
14991  2019-07-20T08:39:55.001007Z  benign      0  4.200429  491.169769
14992 2019-07-20T08:39:56.0050048Z  benign      0  4.253915  491.405273
14993 2019-07-20T08:39:57.0050048Z  benign      0  4.303558  492.308100
14994 2019-07-20T08:39:58.0050048Z  benign      0  4.323736  492.465100
14995  2019-07-20T08:39:59.004013Z  benign      0  4.323736  492.896881

       MV 101  P1_STATE  P101 Status  P102 Status     AIT 201  …  \
0           1         3            2            1  142.527557  …
1           1         3            2            1  142.527557  …
```

```
2            1          3            2            1  142.527557  …
3            1          3            2            1  142.527557  …
4            1          3            2            1  142.527557  …
…       …       …          …          …         …  …
14991        2          2            2            1  131.408615  …
14992        2          2            2            1  131.408615  …
14993        2          2            2            1  131.408615  …
14994        2          2            2            1  131.408615  …
14995        2          2            2            1  131.408615  …

                                                  LSH 601  \
0      {u'IsSystem': False, u'Name': u'Active', u'Val…
1      {u'IsSystem': False, u'Name': u'Active', u'Val…
2      {u'IsSystem': False, u'Name': u'Active', u'Val…
3      {u'IsSystem': False, u'Name': u'Active', u'Val…
4      {u'IsSystem': False, u'Name': u'Active', u'Val…
…                                                   …
14991  {u'IsSystem': False, u'Name': u'Active', u'Val…
14992  {u'IsSystem': False, u'Name': u'Active', u'Val…
14993  {u'IsSystem': False, u'Name': u'Active', u'Val…
14994  {u'IsSystem': False, u'Name': u'Active', u'Val…
14995  {u'IsSystem': False, u'Name': u'Active', u'Val…

                                                  LSH 602  \
0      {u'IsSystem': False, u'Name': u'Active', u'Val…
1      {u'IsSystem': False, u'Name': u'Active', u'Val…
2      {u'IsSystem': False, u'Name': u'Active', u'Val…
3      {u'IsSystem': False, u'Name': u'Active', u'Val…
4      {u'IsSystem': False, u'Name': u'Active', u'Val…
…                                                   …
14991  {u'IsSystem': False, u'Name': u'Active', u'Val…
14992  {u'IsSystem': False, u'Name': u'Active', u'Val…
14993  {u'IsSystem': False, u'Name': u'Active', u'Val…
14994  {u'IsSystem': False, u'Name': u'Active', u'Val…
14995  {u'IsSystem': False, u'Name': u'Active', u'Val…

                                                  LSH 603  \
0      {u'IsSystem': False, u'Name': u'Inactive', u'V…
1      {u'IsSystem': False, u'Name': u'Inactive', u'V…
2      {u'IsSystem': False, u'Name': u'Inactive', u'V…
3      {u'IsSystem': False, u'Name': u'Inactive', u'V…
4      {u'IsSystem': False, u'Name': u'Inactive', u'V…
…                                                   …
14991  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14992  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14993  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14994  {u'IsSystem': False, u'Name': u'Inactive', u'V…
```

```
14995  {u'IsSystem': False, u'Name': u'Inactive', u'V…

                                                 LSL 601  \
0      {u'IsSystem': False, u'Name': u'Inactive', u'V…
1      {u'IsSystem': False, u'Name': u'Inactive', u'V…
2      {u'IsSystem': False, u'Name': u'Inactive', u'V…
3      {u'IsSystem': False, u'Name': u'Inactive', u'V…
4      {u'IsSystem': False, u'Name': u'Inactive', u'V…
…                                                  …
14991  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14992  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14993  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14994  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14995  {u'IsSystem': False, u'Name': u'Inactive', u'V…

                                                 LSL 602  \
0      {u'IsSystem': False, u'Name': u'Inactive', u'V…
1      {u'IsSystem': False, u'Name': u'Inactive', u'V…
2      {u'IsSystem': False, u'Name': u'Inactive', u'V…
3      {u'IsSystem': False, u'Name': u'Inactive', u'V…
4      {u'IsSystem': False, u'Name': u'Inactive', u'V…
…                                                  …
14991  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14992  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14993  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14994  {u'IsSystem': False, u'Name': u'Inactive', u'V…
14995  {u'IsSystem': False, u'Name': u'Inactive', u'V…

                                                 LSL 603 P6 STATE  \
0      {u'IsSystem': False, u'Name': u'Active', u'Val…        2
1      {u'IsSystem': False, u'Name': u'Active', u'Val…        2
2      {u'IsSystem': False, u'Name': u'Active', u'Val…        2
3      {u'IsSystem': False, u'Name': u'Active', u'Val…        2
4      {u'IsSystem': False, u'Name': u'Active', u'Val…        2
…                                                  …      …
14991  {u'IsSystem': False, u'Name': u'Active', u'Val…        2
14992  {u'IsSystem': False, u'Name': u'Active', u'Val…        2
14993  {u'IsSystem': False, u'Name': u'Active', u'Val…        2
14994  {u'IsSystem': False, u'Name': u'Active', u'Val…        2
14995  {u'IsSystem': False, u'Name': u'Active', u'Val…        2

       P601 Status  P602 Status  P603 Status
0                1            1            1
1                1            1            1
2                1            1            1
3                1            1            1
4                1            1            1
```

```
…               …           …           …
14991             1           1           1
14992             1           1           1
14993             1           1           1
14994             1           1           1
14995             1           1           1

[14996 rows x 80 columns]
```

[30]:

```
df.columns
```

[30]:

```
Index(['GMT +0', 'Attack', 'Label', 'FIT 101', 'LIT 101', 'MV 101', 'P1_STATE',
       'P101 Status', 'P102 Status', 'AIT 201', 'AIT 202', 'AIT 203',
       'FIT 201', 'LS 201', 'LS 202', 'LSL 203', 'LSLL 203', 'MV201',
       'P2_STATE', 'P201 Status', 'P202 Status', 'P203 Status', 'P204 Status',
       'P205 Status', 'P206 Status', 'P207 Status', 'P208 Status', 'AIT 301',
       'AIT 302', 'AIT 303', 'DPIT 301', 'FIT 301', 'LIT 301', 'MV 301',
       'MV 302', 'MV 303', 'MV 304', 'P3_STATE', 'P301 Status', 'P302 Status',
       'AIT 401', 'AIT 402', 'FIT 401', 'LIT 401', 'LS 401', 'P4_STATE',
       'P401 Status', 'P402 Status', 'P403 Status', 'P404 Status', 'UV401',
       'AIT 501', 'AIT 502', 'AIT 503', 'AIT 504', 'FIT 501', 'FIT 502',
       'FIT 503', 'FIT 504', 'MV 501', 'MV 502', 'MV 503', 'MV 504',
       'P5_STATE', 'P501 Status', 'P502 Status', 'PIT 501', 'PIT 502',
       'PIT 503', 'FIT 601', 'LSH 601', 'LSH 602', 'LSH 603', 'LSL 601',
       'LSL 602', 'LSL 603', 'P6 STATE', 'P601 Status', 'P602 Status',
       'P603 Status'],
      dtype='object')
```

Function to preprocess the data using StandardScaler

[31]:

```
def preprocess_data(data):
    """
    Prepare SWAT dataset for adversarial attacks
    """
    # Drop timestamp column and separate features/labels
    X = data.drop(['GMT +0', 'Attack', 'Label'], axis=1)
    y = data['Label']

    # Scale the features
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)

    # Split the data
    X_train, X_test, y_train, y_test = train_test_split(
        X_scaled, y, test_size=0.2, random_state=42
    )
```

```
    return X_train, X_test, y_train, y_test, scaler, X.columns
```

FGSM (Fast Gradient Sign Method) function which apply the formula on data

[32]:
```
def fgsm_attack(data, epsilon, gradient):
    """Performs a Fast Gradient Sign Method attack."""
    return data + epsilon * np.sign(gradient)
```

[33]:
```
def fast_gradient_sign_method(model, X, eps=0.3):
    """
    Implementation of FGSM attack
    Based on the gradient-based attacks discussed in the slides
    """
    X_perturbed = X.copy()
    probs = model.predict_proba(X)

    for i in range(X.shape[0]):
        # predicted class
        target = np.argmax(probs[i])

        # compute gradient using finite differences
        grad = np.zeros(X.shape[1])
        for j in range(X.shape[1]):
            X_temp = X[i].copy()
            X_temp[j] += eps
            prob_plus = model.predict_proba(X_temp.reshape(1, -1))[0][target]

            X_temp = X[i].copy()
            X_temp[j] -= eps
            prob_minus = model.predict_proba(X_temp.reshape(1, -1))[0][target]

            grad[j] = (prob_plus - prob_minus) / (2 * eps)

        # apply perturbation
        X_perturbed[i] = fgsm_attack(X_perturbed[i], eps, grad)

    return X_perturbed
```

1 MLPClassifier & FGSM

[34]:
```
def map_df_num(df: pd.DataFrame) -> pd.DataFrame:
    new_df = df.applymap(lambda x: 1 if isinstance(x, str) and "inactive" in x.
 ↪lower()
                        else 0 if isinstance(x, str) and "active" in x.lower()
                        else x).copy()
```

```
    return new_df
```

1.0.1 Data preprocessing

[35]:
```
df = map_df_num(df)
X_train, X_test, y_train, y_test, scaler, feature_names = preprocess_data(df)
```

```
/tmp/ipykernel_328889/1147833406.py:2: FutureWarning: DataFrame.applymap has
been deprecated. Use DataFrame.map instead.
  new_df = df.applymap(lambda x: 1 if isinstance(x, str) and "inactive" in
x.lower()
```

[36]:
```
model = MLPClassifier(
    hidden_layer_sizes=(100, 50),
    max_iter=300,
    random_state=42
)
model.fit(X_train, y_train)
```

[36]:
```
MLPClassifier(hidden_layer_sizes=(100, 50), max_iter=300, random_state=42)
```

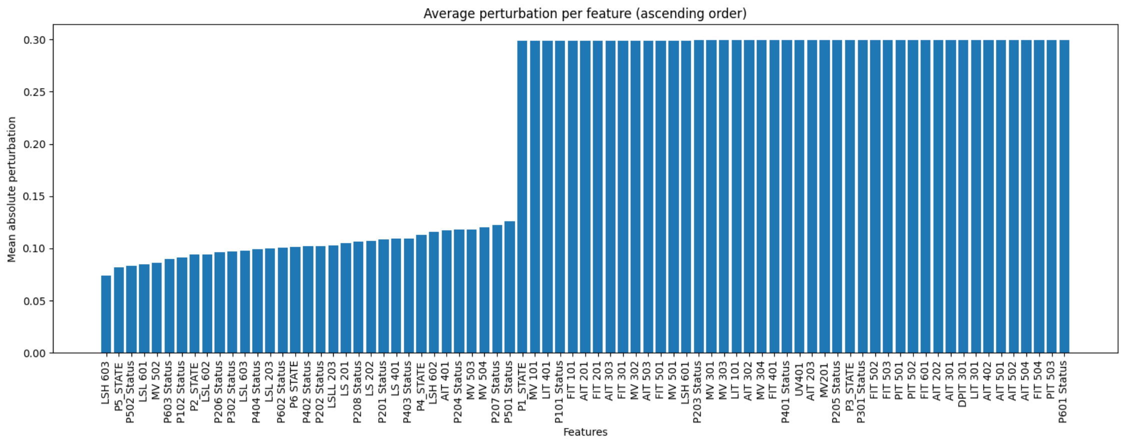
[37]:
```
X_perturbed = fast_gradient_sign_method(model, X_test)
```

1.1 Analysis

Showing the perturbation per features, to show columns more likely to be attacked

[38]:
```
# retrieve feature perturbation
mean_perturbation = np.mean(np.abs(X_perturbed - X_test), axis=0)

perturbation_dict = dict(zip(feature_names, mean_perturbation))

# Sort the dictionary by perturbations
sorted_perturbations = dict(sorted(perturbation_dict.items(), key=lambda x:␣
 ↪x[1]))

sorted_features = list(sorted_perturbations.keys())
sorted_values = list(sorted_perturbations.values())
```

[39]:
```
plt.figure(figsize=(15, 6))
plt.bar(range(len(sorted_features)), sorted_values)
plt.xticks(range(len(sorted_features)), sorted_features, rotation=90)
plt.title('Average perturbation per feature (ascending order)')
plt.xlabel('Features')
plt.ylabel('Mean absolute perturbation')
plt.tight_layout()
plt.show()
```



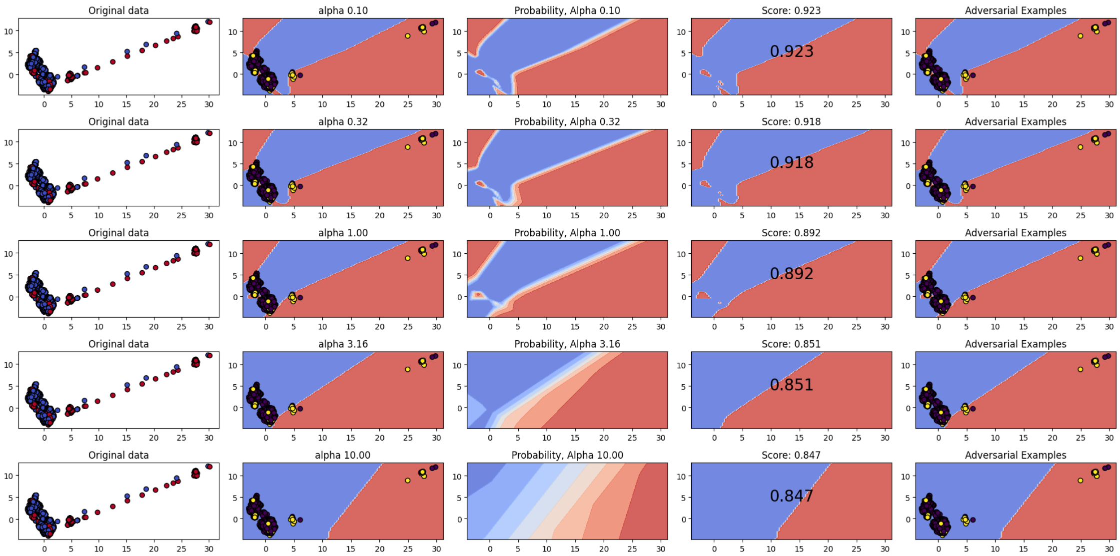
Reducing dimensions to 2 using PCA for visualization

[40]:
```
pca = PCA(n_components=2, random_state=42)
X_train_2d = pca.fit_transform(X_train)
X_test_2d = pca.transform(X_test)
```

Showing decision boundary with different values of alpha

[41]:
```
alphas = [0.1, 0.32, 1.0, 3.16, 10.0]

fig, axes = plt.subplots(len(alphas), 5, figsize=(20, 10))

for i, alpha in enumerate(alphas):
    # mlp training
    clf = MLPClassifier(
        alpha=alpha,
        hidden_layer_sizes=(100, 50),
        max_iter=300,
        random_state=42
    )
    clf.fit(X_train_2d, y_train)

    # 2D mesh grid -> plotting decision boundaries
    x_min, x_max = X_train_2d[:, 0].min() - 1, X_train_2d[:, 0].max() + 1
    y_min, y_max = X_train_2d[:, 1].min() - 1, X_train_2d[:, 1].max() + 1
    xx, yy = np.meshgrid(
        np.linspace(x_min, x_max, 100),
        np.linspace(y_min, y_max, 100
    ))

    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
```

```python
    # display original data
    ax = axes[i, 0]
    ax.scatter(X_train_2d[:, 0], X_train_2d[:, 1], c=y_train, cmap=plt.cm.coolwarm, edgecolor='k')
    ax.set_title('Original data')

    # display decision boundary
    ax = axes[i, 1]
    ax.contourf(xx, yy, Z, alpha=0.8, cmap=plt.cm.coolwarm)
    ax.scatter(X_test_2d[:, 0], X_test_2d[:, 1], c=y_test, edgecolor='k', marker='o')
    ax.set_title(f'alpha {alpha:.2f}')

    # display decision regions
    ax = axes[i, 2]
    prob = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
    ax.contourf(xx, yy, prob.reshape(xx.shape), alpha=0.8, cmap=plt.cm.coolwarm)
    ax.set_title(f'Probability, Alpha {alpha:.2f}')

    # display decision margins
    ax = axes[i, 3]
    score = clf.score(X_test_2d, y_test)
    ax.contourf(xx, yy, Z, alpha=0.8, cmap=plt.cm.coolwarm)
    ax.text(0.5, 0.5, f'{score:.3f}', fontsize=20, ha='center', transform=ax.transAxes)
    ax.set_title(f'Score: {score:.3f}')

    # test with feature perturbations
    ax = axes[i, 4]
    ax.contourf(xx, yy, Z, alpha=0.8, cmap=plt.cm.coolwarm)
    ax.scatter(X_test_2d[:, 0], X_test_2d[:, 1], c=y_test, edgecolor='k', marker='o')
    ax.set_title('Adversarial Examples')

plt.tight_layout()
plt.show()
```



1.1.1 The key insights we can see from these visualizations are:

- **Regularization trade-off:** As alpha increases, we see a clear trade-off between model complexity and accuracy. Choosing a lower alpha value (0.1, 0.32) allow more complex decision boundaries and achieve higher accuracy, while higher alpha values (3.16, 10.0) force simpler boundaries but reduce accuracy.
- **Model robustness:** The smoother decision boundaries at higher alpha values might make the model more robust to noise and adversarial attacks, despite the lower accuracy.

We can say that this representation demonstrate how regularization strength affects a the neural network's decision-making process and the resulting impact on its performance and robustness.

2 RandomForestClassifier & FGSM

Let's prepare the data again and encode the labels

[42]:
```
data = df.copy()

# labels encoding
label_encoder = LabelEncoder()
data['Label'] = label_encoder.fit_transform(data['Label'])

X_train, X_test, y_train, y_test, scaler, features = preprocess_data(data)
```

As you saw in the title, we are going to train a random forest classifier

[43]:
```
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)
```

[43]: RandomForestClassifier(random_state=42)

2.1 Analysis

[44]:
```
y_pred = clf.predict(X_test)
clean_accuracy = accuracy_score(y_test, y_pred)
print(f"Clean accuracy: {clean_accuracy:.2f}")
```

```
Clean accuracy: 1.00
```

Now, we are going to add perturbations inside the input data and see how the model predictions react

[45]:
```
epsilon = 0.1
gradients = X_test - X_train.mean(axis=0)  # Simplified gradient
X_test_adv = fgsm_attack(X_test, epsilon, gradients)
```

Let's evaluate the adversarial accuracy

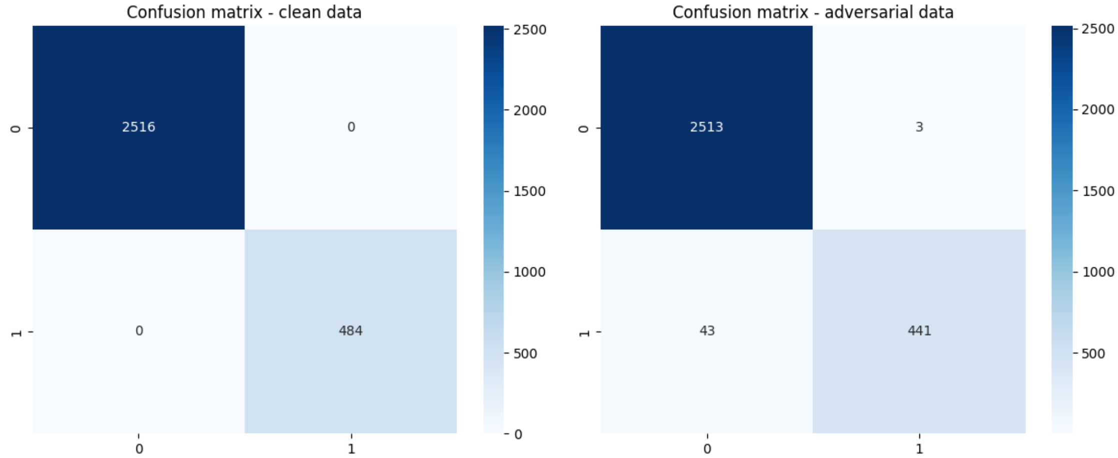
[46]:
```
y_pred_adv = clf.predict(X_test_adv)
adversarial_accuracy = accuracy_score(y_test, y_pred_adv)
print(f"Adversarial accuracy: {adversarial_accuracy:.2f}")
```

```
Adversarial accuracy: 0.98
```

We can see that the model isn't as efficient as before in its predictions.

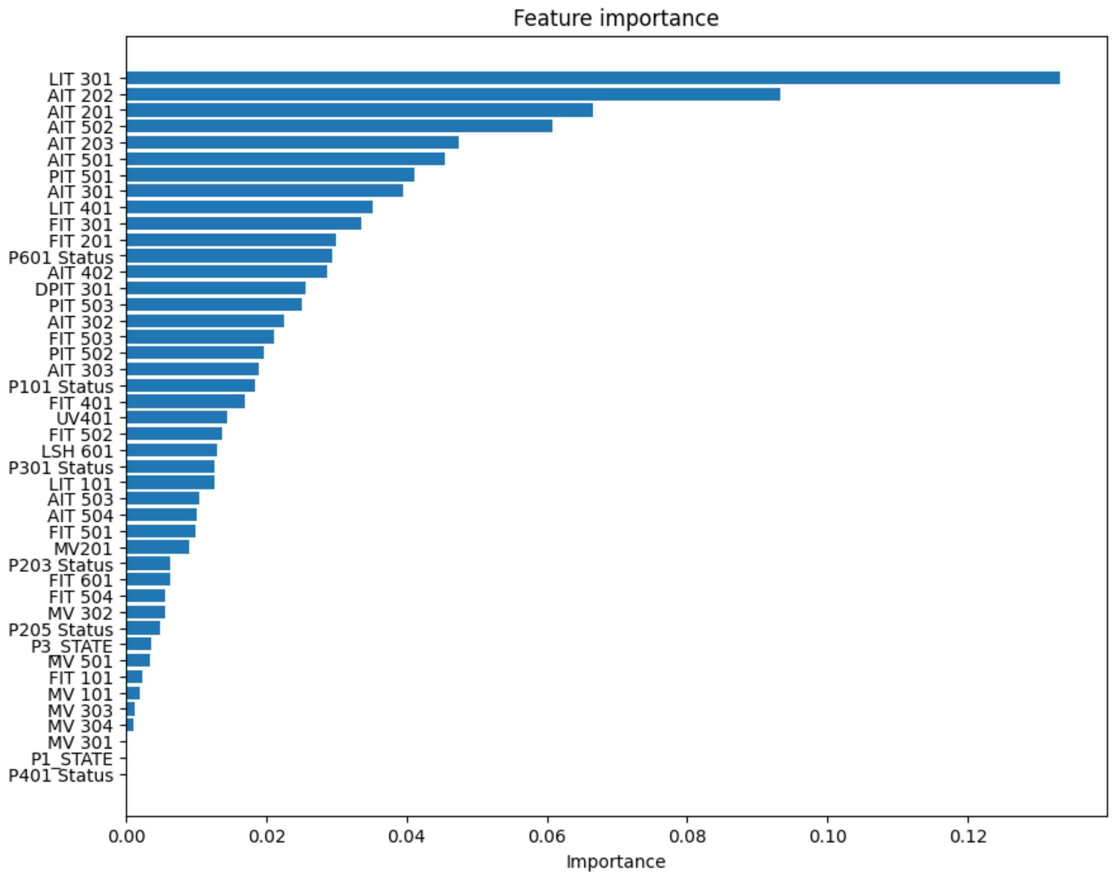
A better visualization is given by:

[47]:
```
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
cm_clean = confusion_matrix(y_test, y_pred)
sns.heatmap(cm_clean, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion matrix - clean data')

plt.subplot(1, 2, 2)
cm_perturbed = confusion_matrix(y_test, y_pred_adv)
sns.heatmap(cm_perturbed, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion matrix - adversarial data')

plt.tight_layout()
plt.show()
```



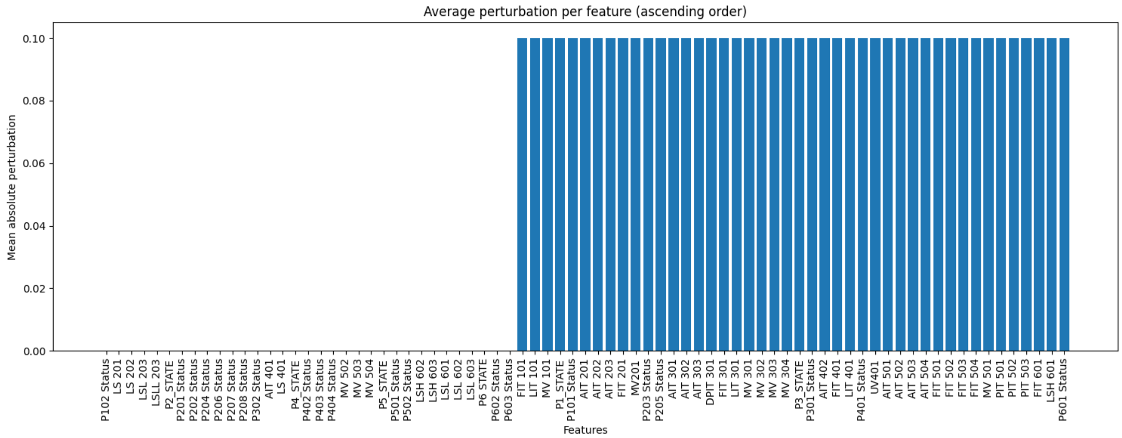
Let's analyze the feature importance in the prediction (modifications on those labels can highly disturb our model predictions)

[48]:
```
feature_importance = clf.feature_importances_

# filter out features with 0 importance
non_zero_idx = feature_importance > 0

sorted_idx = np.argsort(feature_importance[non_zero_idx])
plt.figure(figsize=(10, 8))
plt.barh(range(len(features[non_zero_idx])),
  ↪feature_importance[non_zero_idx][sorted_idx], align='center')
plt.yticks(np.arange(len(features[non_zero_idx])),
  ↪features[non_zero_idx][sorted_idx])
plt.xlabel('Importance')
plt.title('Feature importance')
plt.show()
```



To go further, we can compute and display the average perturbation on the predictions between clean and noisy data.

[49]:
```
mean_perturbation = np.mean(np.abs(X_test_adv - X_test), axis=0)

# create the dict for perturbations
perturbation_dict = dict(zip(feature_names, mean_perturbation))
sorted_perturbations = dict(sorted(perturbation_dict.items(), key=lambda x:␣
↪x[1]))
sorted_features = list(sorted_perturbations.keys())
sorted_values = list(sorted_perturbations.values())

plt.figure(figsize=(15, 6))
plt.bar(range(len(sorted_features)), sorted_values)
plt.xticks(range(len(sorted_features)), sorted_features, rotation=90)
plt.title('Average perturbation per feature (ascending order)')
plt.xlabel('Features')
plt.ylabel('Mean absolute perturbation')
plt.tight_layout()
plt.show()
```



As we can see, for some features the noise doesn't change the predictions.

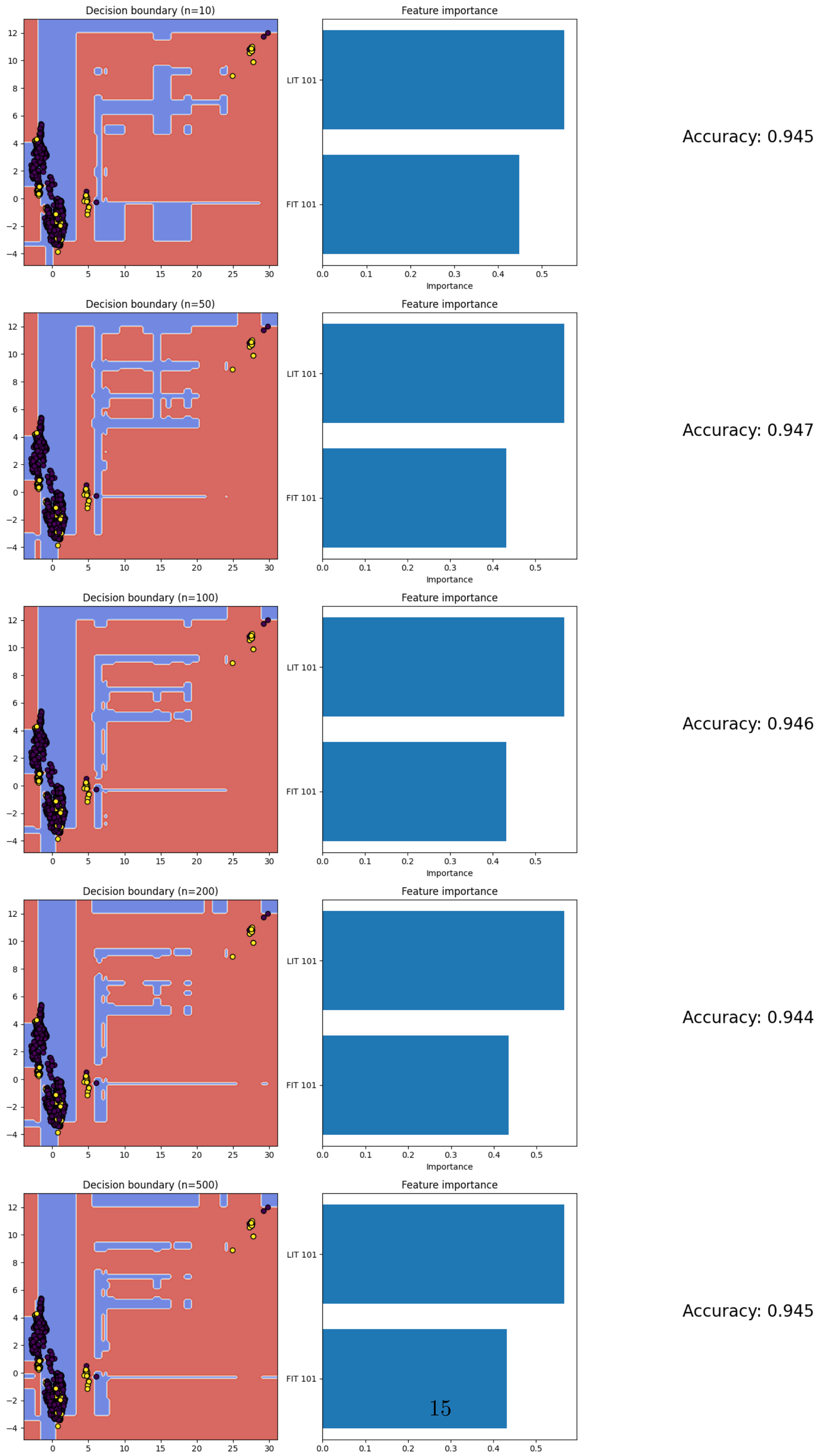
Reducing dimensions to 2 using PCA for visualization.

```
[50]: pca = PCA(n_components=2, random_state=42)
X_train_2d = pca.fit_transform(X_train)
X_test_2d = pca.transform(X_test)
```

Showing decision boundary with different values of n_estimators

```
[53]: n_estimators_list = [10, 50, 100, 200, 500]

fig, axes = plt.subplots(len(n_estimators_list), 3, figsize=(15,␣
 ↪len(n_estimators_list) * 5))

for i, n_estimators in enumerate(n_estimators_list):

    # RandomForest training
    clf = RandomForestClassifier(n_estimators=n_estimators, random_state=42)
    clf.fit(X_train_2d, y_train)

    # 2D mesh grid -> plotting decision boundaries
    x_min, x_max = X_train_2d[:, 0].min() - 1, X_train_2d[:, 0].max() + 1
    y_min, y_max = X_train_2d[:, 1].min() - 1, X_train_2d[:, 1].max() + 1
    xx, yy = np.meshgrid(np.linspace(x_min, x_max, 100),
                         np.linspace(y_min, y_max, 100))
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    ax = axes[i, 0]
    ax.contourf(xx, yy, Z, alpha=0.8, cmap=plt.cm.coolwarm)
    ax.scatter(X_test_2d[:, 0], X_test_2d[:, 1], c=y_test, edgecolor='k',␣
 ↪marker='o')
```

```
    ax.set_title(f'Decision boundary (n={n_estimators})')

    # plot feature importance
    feature_importance = clf.feature_importances_
    sorted_idx = np.argsort(feature_importance)
    ax = axes[i, 1]
    ax.barh(range(len(sorted_idx)), feature_importance[sorted_idx],␣
↪align='center')
    ax.set_yticks(range(len(sorted_idx)))
    ax.set_yticklabels(np.array(features)[sorted_idx])
    ax.set_xlabel('Importance')
    ax.set_title('Feature importance')

    # show accuracy
    score = clf.score(X_test_2d, y_test)
    ax = axes[i, 2]
    ax.text(0.5, 0.5, f'Accuracy: {score:.3f}', fontsize=20, ha='center',␣
↪transform=ax.transAxes)
    ax.axis('off')

plt.tight_layout()
plt.show()
```


Decision boundary (n=10)
Feature importance
LIT 101
FIT 101
Importance
Accuracy: 0.945
Decision boundary (n=50)
Feature importance
LIT 101
FIT 101
Importance
Accuracy: 0.947
Decision boundary (n=100)
Feature importance
LIT 101
FIT 101
Importance
Accuracy: 0.946
Decision boundary (n=200)
Feature importance
LIT 101
FIT 101
Importance
Accuracy: 0.944
Decision boundary (n=500)
Feature importance
LIT 101
FIT 101
Importance
Accuracy: 0.945