17_intro_to_computer-vision

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CPSC 330
Applied Machine Learning

1 Lecture 17: Multi-class classification and introduction to computer vision

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1.1 Imports

[1]:
```
import glob
import os

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from sklearn import datasets
from sklearn.dummy import DummyClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.metrics import (
    classification_report,
    confusion_matrix,
    plot_confusion_matrix,
)
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.svm import SVC
```

1.2 Learning objectives

- Apply classifiers to multi-class classification algorithms.

- Explain the role of neural networks in machine learning, and the pros/cons of using them.
- Explain why the methods we've learned previously would not be effective on image data.
- Apply pre-trained neural networks to classification and regression problems.
- Utilize pre-trained networks as feature extractors and combine them with models we've learned previously.

1.3 Recap

1.3.1 True/False questions

1. Word representation created by term-term co-occurrence matrix are long and sparse whereas the ones created by Word2Vec are short and dense. **TRUE**
2. It's possible to use word representations for text classification instead of bag-of-words representation. **TRUE**

1.3.2 Questions for discussion

- Given the following table, which word pair is more similar in terms of dot product: (word 1, word 2) or (word 1, word 3)?

	data	fashion	model
word 1	10	0	8
word 2	0	8	3
word 3	6	1	4

1.3.3 True/False questions

1. The topic model approach we used in the last lecture, Latent Dirichlet Allocation (LDA), is an unsupervised approach. **TRUE**
2. In an LDA topic model, the same word can be associated with two different topics with high probability. **TRUE** Not a document. But a word definitely can.
3. If I train a topic model on a large collection of news articles with K = 10, I would get 10 topic labels (e.g., sports, culture, politics, finance) as output. **FALSE** A topic model doesn't produce labels.

1.4 Multi-class, meta-strategies

- So far we have been talking about binary classification
- Can we use these classifiers when there are more than two classes?
  - "ImageNet" computer vision competition, for example, has 1000 classes
- Can we use decision trees or KNNs for multi-class classification?
- What about logistic regression and Linear SVMs?

- Many linear classification models don't extend naturally to the multiclass case.
- A common technique is to reduce multiclass classication into several instances of binary classification problems.
- Two kind of "hacky" ways to reduce multi-class classification into binary classification:
  - the one-vs.-rest approach
  - the one-vs.-one approach

Note There is also a **multinomial** logistic regression also known as **the maxent classifier**. This is different than the above multi-class meta strategies. More on this in DSCI 573.

1.4.1 One vs. Rest approach

- 1v{2,3}, 2v{1,3}, 3v{1,2}
- Learn a binary model for each class which tries to separate that class from all of the other classes.
- If you have k classes, it'll train k binary classifiers, one for each class.
- Trained on imbalanced datasets containing all examples.
- Given a test point, get scores from all binary classifiers (e.g., raw scores for logistic regression).

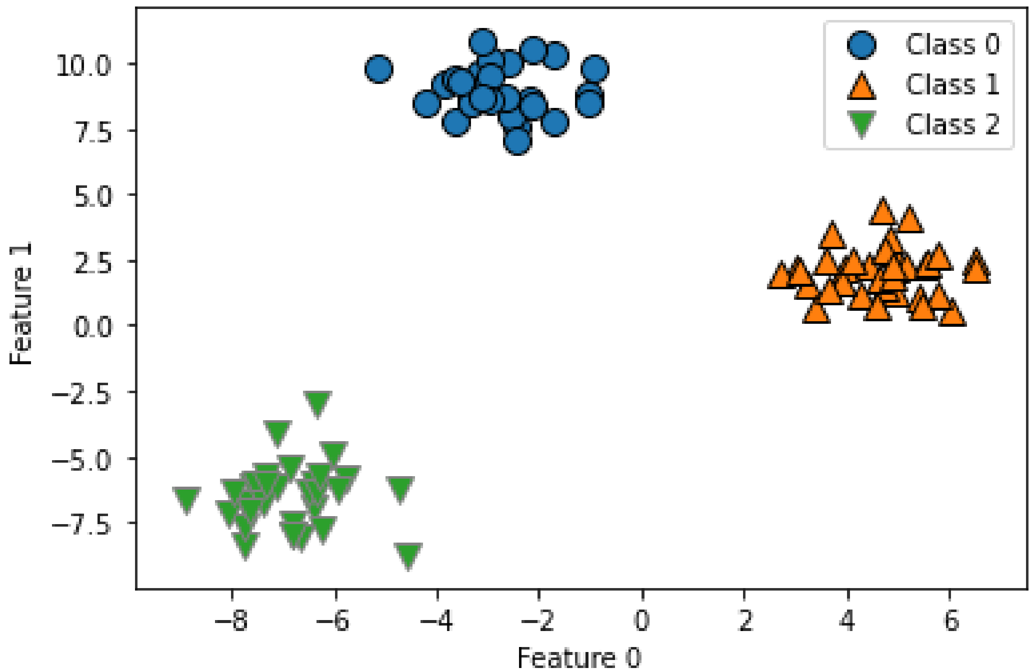
1.4.2 One Vs. Rest prediction

- The classifier which has the highest score for this class "**wins**" and that's going to be the prediction for this class.

- Since we have one binary classifier per class, for each class, we have coefficients per feature and an intercept.

Let's create some synthetic data with two features and three classes.

[2]:
```
import mglearn
from sklearn.datasets import make_blobs

X, y = make_blobs(centers=3, n_samples=120, random_state=42)
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=123
)
mglearn.discrete_scatter(X_train[:, 0], X_train[:, 1], y_train)
plt.xlabel("Feature 0")
plt.ylabel("Feature 1")
plt.legend(["Class 0", "Class 1", "Class 2"]);
```



[3]:
```
lr = LogisticRegression(max_iter=2000, multi_class="ovr")
lr.fit(X_train, y_train)
print("Coefficient shape: ", lr.coef_.shape)
print("Intercept shape: ", lr.intercept_.shape)
```

```
Coefficient shape:  (3, 2)
Intercept shape:  (3,)
```

[4]:
```
pd.DataFrame(
    lr.coef_, columns=['Feature 1', 'Feature 2']).assign(Intercept=lr.
 ↪intercept_)
```

[4]:

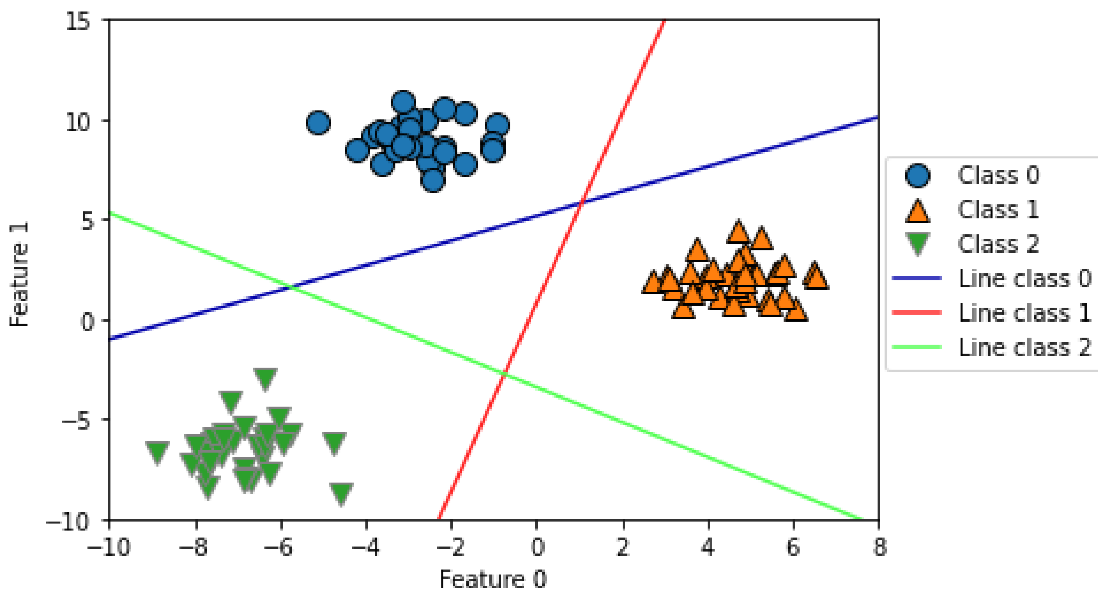
	Feature 1	Feature 2	Intercept
0	-0.651233	1.053612	-5.426267
1	1.354180	-0.286475	0.216166
2	-0.633207	-0.725136	-2.469413

- This learns three binary linear models.
- So we have coefficients for two features for each of these three linear models.
- Also we have three intercepts, one for each class.

Code credit

[5]:
```
mglearn.discrete_scatter(X_train[:, 0], X_train[:, 1], y_train)
line_x = np.linspace(-15, 15)
for coef, intercept, color in zip(lr.coef_, lr.intercept_, mglearn.cm3.colors):
```

```
    line_y = -(line_x * coef[0] + intercept) / coef[1]
    plt.plot(line_x, line_y, c=color)
plt.ylim(-10, 15)
plt.xlim(-10, 8)
plt.xlabel("Feature 0")
plt.ylabel("Feature 1")
plt.legend(
    ["Class 0", "Class 1", "Class 2",
     "Line class 0", "Line class 1", "Line class 2"],
    loc=(1.01, 0.3),
);
```

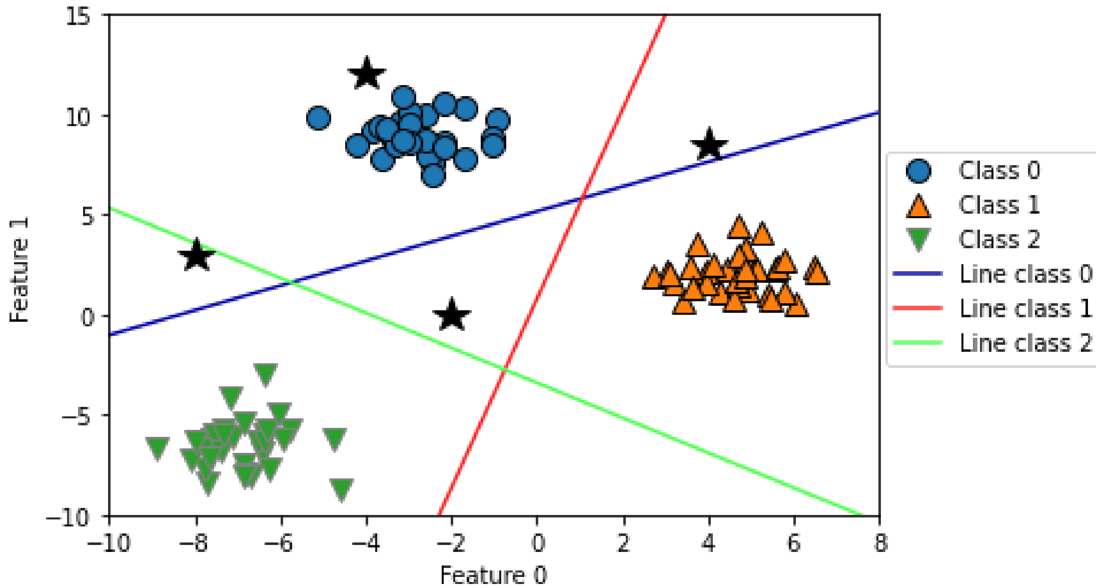


[6]:
```
def plot_test_points():
    test_points = [(-4.0, 12), (-2, 0.0), (-8, 3.0), (4, 8.5)]
    for x, y in test_points:
        plt.plot(x, y, "k*", markersize=16)
```

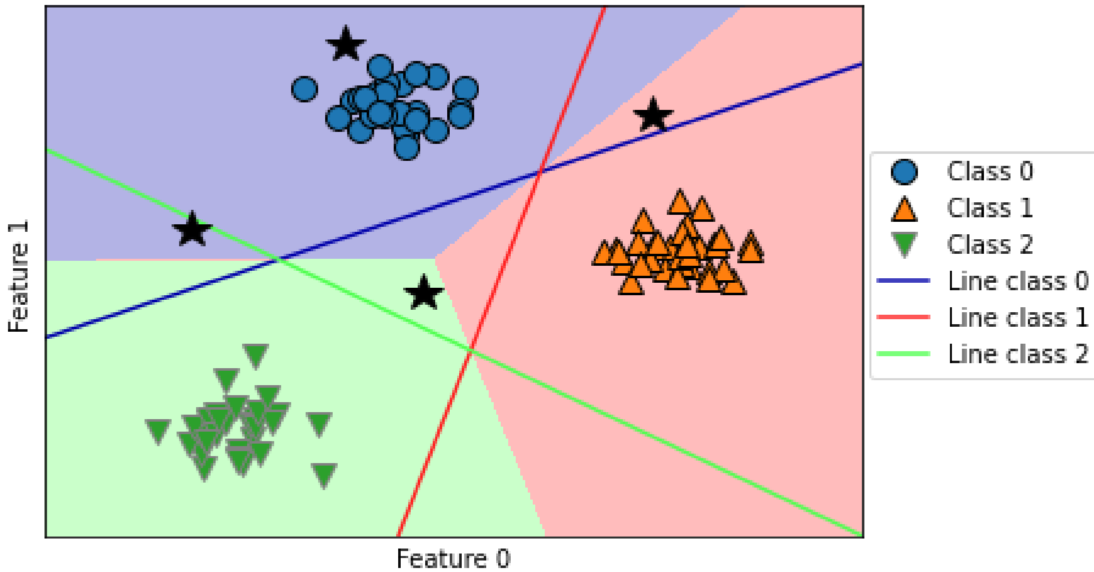
- How would you classify these `test_points`?
  - Pick the class with the **highest value** for the classification formula.

[7]:
```
# You don't have to understand the code.
mglearn.discrete_scatter(X_train[:, 0], X_train[:, 1], y_train)
line_x = np.linspace(-15, 15)
for coef, intercept, color in zip(lr.coef_, lr.intercept_, mglearn.cm3.colors):
    line_y = -(line_x * coef[0] + intercept) / coef[1]
    plt.plot(line_x, line_y, c=color)
plot_test_points()
```

```python
plt.ylim(-10, 15)
plt.xlim(-10, 8)
plt.xlabel("Feature 0")
plt.ylabel("Feature 1")
plt.legend(
    ["Class 0", "Class 1", "Class 2",
     "Line class 0", "Line class 1", "Line class 2"],
    loc=(1.01, 0.3),
);
```



[8]:
```python
# You don't have to understand the code below.
mglearn.plots.plot_2d_classification(lr, X_train, fill=True, alpha=0.3)
mglearn.discrete_scatter(X_train[:, 0], X_train[:, 1], y_train)
line_x = np.linspace(-15, 15)
for coef, intercept, color in zip(lr.coef_, lr.intercept_, mglearn.cm3.colors):
    line_y = -(line_x * coef[0] + intercept) / coef[1]
    plt.plot(line_x, line_y, c=color)
plot_test_points()
plt.legend(
    ["Class 0", "Class 1", "Class 2",
     "Line class 0", "Line class 1", "Line class 2"],
    loc=(1.01, 0.3),
)
plt.xlabel("Feature 0")
plt.ylabel("Feature 1");
```



1.4.3 One Vs. One approach

- Build a binary model for each pair of classes.
- 1v2, 1v3, 2v3
- For k classes, it trains $\frac{k \times (k-1)}{2}$ binary classifiers
- Trained on relatively balanced subsets

1.4.4 One Vs. One prediction

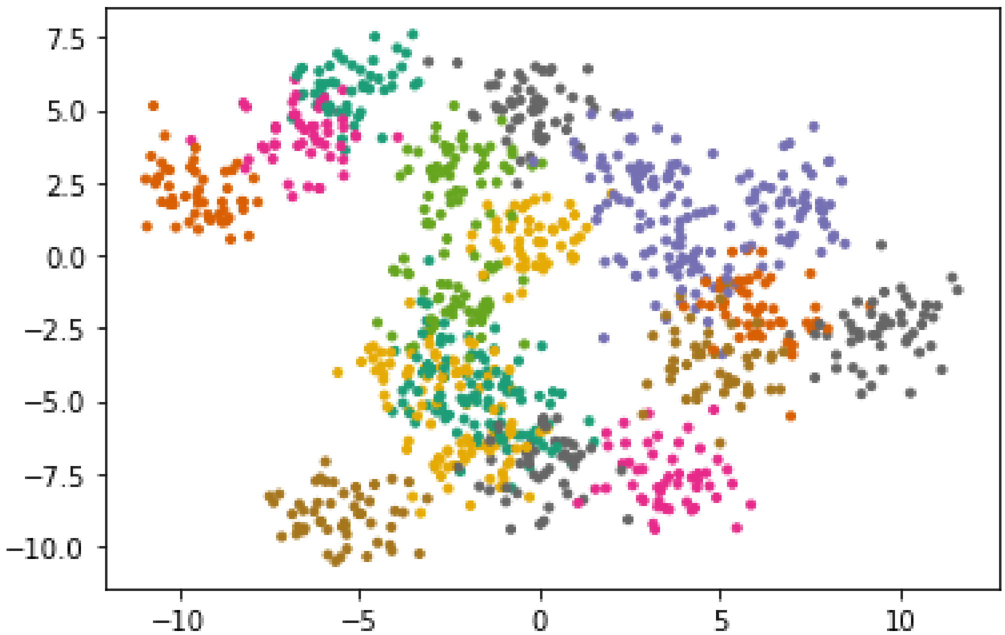
- Apply all of the classifiers on the test example.
- Count how often each class was predicted.
- Predict the class with most **votes**.

1.4.5 Using OneVsRest and OneVsOne as wrappers

- You can use these strategies as meta-strategies for any binary classifiers.
  - `OneVsRestClassifier`
  - `OneVsOneClassifier`
- When do we use `OneVsRestClassifier` or `OneVsOneClassifier`?
- It's not that likely for you to need `OneVsRestClassifier` or `OneVsOneClassifier` because most of the methods you'll use will have native multi-class support.
- However, it's good to know in case you ever need to extend a binary classifier (perhaps one you've implemented on your own).

Let's examine the **time taken** by OneVsRestClassifier and OneVsOneClassifier.

[9]:
```python
from sklearn.multiclass import OneVsOneClassifier, OneVsRestClassifier

# generate blobs with fixed random generator
X_multi, y_multi = make_blobs(n_samples=1000, centers=20, random_state=300)

X_train_multi, X_test_multi, y_train_multi, y_test_multi = train_test_split(
    X_multi, y_multi
)

plt.scatter(*X_multi.T, c=y_multi, marker=".", cmap="Dark2");
```



[10]:
```python
model = OneVsOneClassifier(LogisticRegression())
%timeit model.fit(X_train_multi, y_train_multi);
print("With OVO wrapper")
print(model.score(X_train_multi, y_train_multi))
print(model.score(X_test_multi, y_test_multi))
```

```
930 ms ± 201 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
With OVO wrapper
0.808
0.748
```

[11]:
```python
model = OneVsRestClassifier(LogisticRegression())
%timeit model.fit(X_train_multi, y_train_multi);
print("With OVR wrapper")
print(model.score(X_train_multi, y_train_multi))
```

```python
print(model.score(X_test_multi, y_test_multi))
```

```
362 ms ± 94.8 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
With OVR wrapper
0.728
0.628
```

- As expected OVO takes more time compared to OVR.
- Here you will find summary of how `scikit-learn` handles multi-class classification for different classifiers.

1.4.6 True/False

1. One-vs.-one strategy uses all the available data when training each binary classifier. **FALSE** It uses balanced subsets of the data.
2. For a 100-class classification problem, one-vs.-rest multi-class strategy will create 100 binary classifiers. **TRUE**

1.4.7 Multi-class classification on HappyDB corpus

Let's examine precision, recall, and f1-score of different classes in the HappyDB: "A Corpus of 100,000 Crowdsourced Happy Moments".

[12]:
```python
df = pd.read_csv("data/cleaned_hm.csv", index_col=0)
sample_df = df.dropna()
sample_df.head()
sample_df = sample_df.rename(
    columns={"cleaned_hm": "moment", "ground_truth_category": "target"}
)
sample_df.head()
```

[12]:
```
        wid reflection_period  \
hmid
27676   206               24h
27678    45               24h
27697   498               24h
27705  5732               24h
27715  2272               24h

                                              original_hm  \
hmid
27676  We had a serious talk with some friends of our…
27678                            I meditated last night.
27697  My grandmother start to walk from the bed afte…
27705  I picked my daughter up from the airport and w…
27715        when i received flowers from my best friend

                                                   moment  modified  \
hmid
```

```
27676  We had a serious talk with some friends of our…      True
27678                           I meditated last night.      True
27697  My grandmother start to walk from the bed afte…      True
27705  I picked my daughter up from the airport and w…      True
27715        when i received flowers from my best friend      True

       num_sentence     target predicted_category
hmid
27676             2    bonding            bonding
27678             1    leisure            leisure
27697             1  affection          affection
27705             1    bonding          affection
27715             1    bonding            bonding
```

[13]:
```python
sample_df["target"].value_counts()
```

[13]:
```
affection          4810
achievement        4276
bonding            1750
enjoy_the_moment   1514
leisure            1306
nature              252
exercise            217
Name: target, dtype: int64
```

It's a multiclass classification problem!

[14]:
```python
train_df, test_df = train_test_split(sample_df, test_size=0.3, random_state=123)
X_train_happy, y_train_happy = train_df["moment"], train_df["target"]
X_test_happy, y_test_happy = test_df["moment"], test_df["target"]
```

[15]:
```python
from sklearn.feature_extraction.text import CountVectorizer

pipe_lr = make_pipeline(
    CountVectorizer(stop_words="english"), LogisticRegression(max_iter=2000)
)
```

[16]:
```python
pipe_lr.fit(X_train_happy, y_train_happy);
```

[17]:
```python
preds = pipe_lr.predict(X_test_happy)[:5]
preds
```

[17]:
```
array(['achievement', 'affection', 'bonding', 'enjoy_the_moment',
       'affection'], dtype=object)
```

Note that the output of `predict_proba` now contains a probability for each class:

[18]:
```python
pipe_lr.predict_proba(X_test_happy)[:5]
```

[18]:
```
array([[7.06452307e-01, 3.74990372e-02, 5.65453892e-02, 4.48404513e-02,
        3.05695478e-02, 1.10316043e-01, 1.37772248e-02],
       [4.51072156e-03, 9.89340323e-01, 5.83682148e-04, 3.70785468e-03,
        2.90885880e-04, 6.37026516e-04, 9.29506481e-04],
       [2.13262697e-03, 1.51560025e-02, 9.78843708e-01, 1.36500567e-03,
        1.26026319e-03, 9.41811597e-04, 3.00582288e-04],
       [1.13081120e-01, 9.17845566e-02, 2.38838787e-02, 5.06683802e-01,
        7.30917658e-03, 2.49576657e-01, 7.68080910e-03],
       [7.71874166e-02, 5.53222814e-01, 3.87143050e-02, 8.14784048e-02,
        2.38186758e-02, 2.08421235e-01, 1.71571482e-02]])
```

[19]:
```
pd.DataFrame(pipe_lr.predict_proba(X_test_happy), columns=pipe_lr.classes_).
 ↪head()
```

[19]:

	achievement	affection	bonding	enjoy_the_moment	exercise	leisure	nature
0	0.706452	0.037499	0.056545	0.044840	0.030570	0.110316	0.013777
1	0.004511	0.989340	0.000584	0.003708	0.000291	0.000637	0.000930
2	0.002133	0.015156	0.978844	0.001365	0.001260	0.000942	0.000301
3	0.113081	0.091785	0.023884	0.506684	0.007309	0.249577	0.007681
4	0.077187	0.553223	0.038714	0.081478	0.023819	0.208421	0.017157

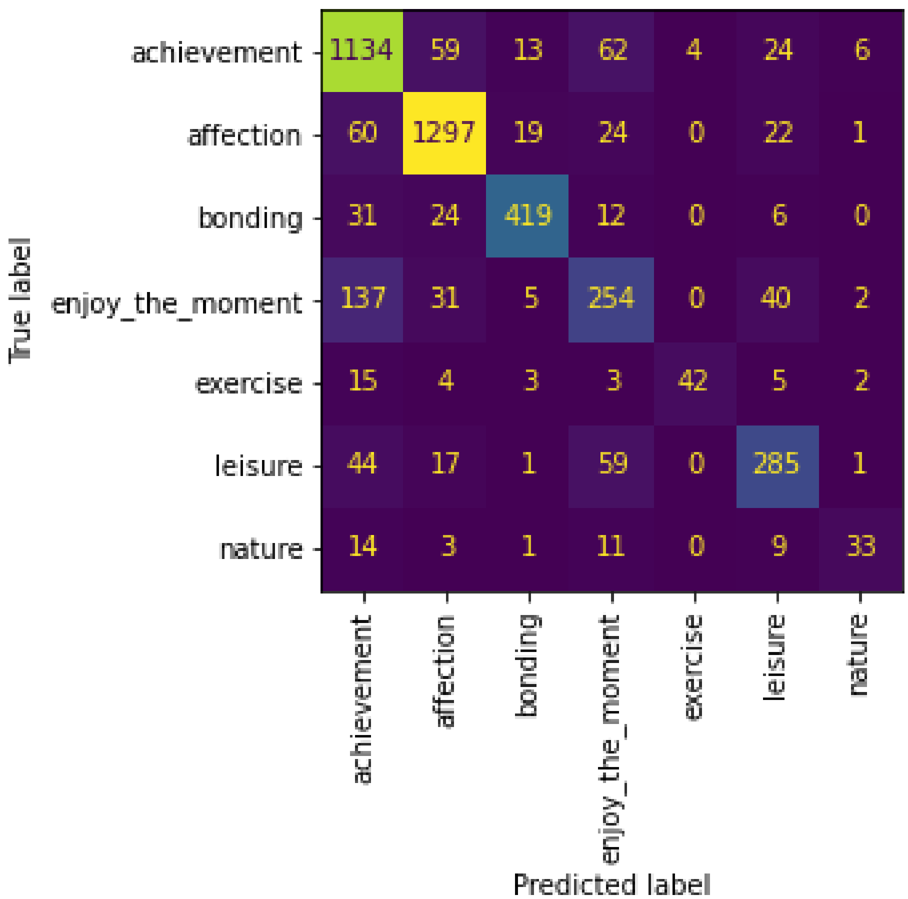
And you'll see that each row adds up to 1, as expected:

[20]:
```
pipe_lr.predict_proba(X_test_happy).sum(axis=1)
```

[20]:
```
array([1., 1., 1., …, 1., 1., 1.])
```

We can also make a confusion matrix:

[21]:
```
from sklearn.metrics import ConfusionMatrixDisplay

disp = ConfusionMatrixDisplay.from_estimator(
    pipe_lr,
    X_test_happy,
    y_test_happy,
    values_format="d",
    xticks_rotation="vertical",
    colorbar=False,
);
```



And print the classification report.

[22]:
```
print(classification_report(y_test_happy, pipe_lr.predict(X_test_happy)))
```

```
                  precision    recall  f1-score   support

     achievement       0.79      0.87      0.83      1302
       affection       0.90      0.91      0.91      1423
         bonding       0.91      0.85      0.88       492
enjoy_the_moment       0.60      0.54      0.57       469
        exercise       0.91      0.57      0.70        74
         leisure       0.73      0.70      0.71       407
          nature       0.73      0.46      0.57        71

        accuracy                           0.82      4238
       macro avg       0.80      0.70      0.74      4238
    weighted avg       0.82      0.82      0.81      4238
```

- Seems like there is a lot of variation in the scores for different classes.

- The model is performing pretty well on *affection* class but not that well on *enjoy_the_moment* and *nature* classes.

How are the predictions made?

[23]:
```
predict_probas = pipe_lr.predict_proba(X_test_happy)
df = pd.DataFrame(predict_probas, columns=pipe_lr.classes_)
df.head()
```

[23]:
```
   achievement  affection   bonding  enjoy_the_moment  exercise   leisure  \
0     0.706452   0.037499  0.056545          0.044840  0.030570  0.110316
1     0.004511   0.989340  0.000584          0.003708  0.000291  0.000637
2     0.002133   0.015156  0.978844          0.001365  0.001260  0.000942
3     0.113081   0.091785  0.023884          0.506684  0.007309  0.249577
4     0.077187   0.553223  0.038714          0.081478  0.023819  0.208421

     nature
0  0.013777
1  0.000930
2  0.000301
3  0.007681
4  0.017157
```

[24]:
```
df['Winner'] = df.idxmax(axis=1)
df.head()
```

[24]:
```
   achievement  affection   bonding  enjoy_the_moment  exercise   leisure  \
0     0.706452   0.037499  0.056545          0.044840  0.030570  0.110316
1     0.004511   0.989340  0.000584          0.003708  0.000291  0.000637
2     0.002133   0.015156  0.978844          0.001365  0.001260  0.000942
3     0.113081   0.091785  0.023884          0.506684  0.007309  0.249577
4     0.077187   0.553223  0.038714          0.081478  0.023819  0.208421

     nature            Winner
0  0.013777       achievement
1  0.000930         affection
2  0.000301           bonding
3  0.007681  enjoy_the_moment
4  0.017157         affection
```

[25]:
```
df['Predict'] = pipe_lr.predict(X_test_happy)
df.head()
```

[25]:
```
   achievement  affection   bonding  enjoy_the_moment  exercise   leisure  \
0     0.706452   0.037499  0.056545          0.044840  0.030570  0.110316
1     0.004511   0.989340  0.000584          0.003708  0.000291  0.000637
2     0.002133   0.015156  0.978844          0.001365  0.001260  0.000942
3     0.113081   0.091785  0.023884          0.506684  0.007309  0.249577
```

```
4     0.077187   0.553223  0.038714          0.081478  0.023819  0.208421

     nature            Winner           Predict
0  0.013777       achievement       achievement
1  0.000930         affection         affection
2  0.000301           bonding           bonding
3  0.007681  enjoy_the_moment  enjoy_the_moment
4  0.017157         affection         affection
```

Now, confirm our manual calculation (`Winner`) and auto calculation (`Predict`) are equal on every row:

[26]:
```python
df['Winner'].equals(df['Predict'])
```

[26]:
```
True
```

How many coefficients have we learned?

[27]:
```python
pipe_lr.named_steps["logisticregression"].coef_.shape
```

[27]:
```
(7, 8060)
```

- We have one coefficient per feature *per class*.
- Let's examine them.

[28]:
```python
feature_names = pipe_lr.named_steps["countvectorizer"].get_feature_names_out()
lr_coefs = pd.DataFrame(
    data=pipe_lr.named_steps["logisticregression"].coef_.T,
    index=feature_names,
    columns=pipe_lr.classes_,
).sort_values("bonding", ascending=False)
lr_coefs
```

[28]:
```
           achievement  affection   bonding  enjoy_the_moment  exercise  \
friend       -1.687508  -0.183475  5.589816         -1.707884  0.330449
friends      -1.304138   0.052716  5.246049         -1.992706  0.328852
roommate     -1.327173  -0.690690  3.418162         -1.138268 -0.078645
coworkers    -0.588489  -0.606159  3.011448         -1.098920 -0.088529
coworker     -0.934815  -0.591283  2.770895         -0.560367 -0.093261
…                  …          …        …                …         …
feelings      0.057263   1.195037 -0.898350         -0.123819 -0.103988
jogging      -0.046356  -0.319891 -0.909223         -0.098751  1.521339
telling      -0.436985   0.870927 -1.070989          0.694236 -0.066820
drive        -0.150849   0.584471 -1.184907          0.891981 -0.239564
boy           1.398697   0.288216 -1.327457          0.138855 -0.261439

            leisure    nature
friend    -1.769275 -0.572123
friends   -1.559691 -0.771082
```

```
roommate  -0.070318 -0.113067
coworkers -0.518731 -0.110620
coworker  -0.415518 -0.175651
…              …         …
feelings  -0.093035 -0.033108
jogging   -0.130397 -0.016721
telling    0.038828 -0.029198
drive     -0.453334  0.552202
boy       -0.162193 -0.074679

[8060 rows x 7 columns]
```

The interpretation is a feature importance for predicting a certain class. For example:

[29]:
```
lr_coefs.loc["friend"]
```

[29]:
```
achievement        -1.687508
affection          -0.183475
bonding             5.589816
enjoy_the_moment   -1.707884
exercise            0.330449
leisure            -1.769275
nature             -0.572123
Name: friend, dtype: float64
```

[30]:
```
lr_coefs.loc["friend"].idxmax()
```

[30]:
```
'bonding'
```

- This means that if the value for the feature "friend" is bigger, you are more likely to predict class "bonding".
- If you want a **general feature importance irrespective of class**, you could try looking at the sum of the squares of the coefficients, which is what sklearn does:

[31]:
```
(lr_coefs ** 2).sum(axis=1).sort_values(ascending=False)
```

[31]:
```
friend       4.061112e+01
friends      3.633081e+01
husband      2.764457e+01
wife         2.542290e+01
son          2.361040e+01
                 …
passport     8.849890e-12
rang         8.849890e-12
postman      8.849890e-12
curiosity    8.849890e-12
itching      8.849890e-12
Length: 8060, dtype: float64
```

[32]:

```
?LogisticRegression
```

```
Init signature:
LogisticRegression(
    penalty='l2',
    *,
    dual=False,
    tol=0.0001,
    C=1.0,
    fit_intercept=True,
    intercept_scaling=1,
    class_weight=None,
    random_state=None,
    solver='lbfgs',
    max_iter=100,
    multi_class='auto',
    verbose=0,
    warm_start=False,
    n_jobs=None,
    l1_ratio=None,
)
Docstring:
Logistic Regression (aka logit, MaxEnt) classifier.

In the multiclass case, the training algorithm uses the one-vs-rest (OvR)
scheme if the 'multi_class' option is set to 'ovr', and uses the
cross-entropy loss if the 'multi_class' option is set to 'multinomial'.
(Currently the 'multinomial' option is supported only by the 'lbfgs',
'sag', 'saga' and 'newton-cg' solvers.)

This class implements regularized logistic regression using the
'liblinear' library, 'newton-cg', 'sag', 'saga' and 'lbfgs' solvers. **Note
that regularization is applied by default**. It can handle both dense
and sparse input. Use C-ordered arrays or CSR matrices containing 64-bit
floats for optimal performance; any other input format will be converted
(and copied).

The 'newton-cg', 'sag', and 'lbfgs' solvers support only L2 regularization
with primal formulation, or no regularization. The 'liblinear' solver
supports both L1 and L2 regularization, with a dual formulation only for
the L2 penalty. The Elastic-Net regularization is only supported by the
'saga' solver.

Read more in the :ref:`User Guide <logistic_regression>`.

Parameters
----------
penalty : {'l1', 'l2', 'elasticnet', 'none'}, default='l2'
```

```
    Specify the norm of the penalty:

    - `'none'`: no penalty is added;
    - `'l2'`: add a L2 penalty term and it is the default choice;
    - `'l1'`: add a L1 penalty term;
    - `'elasticnet'`: both L1 and L2 penalty terms are added.

    .. warning::
       Some penalties may not work with some solvers. See the parameter
       `solver` below, to know the compatibility between the penalty and
       solver.

    .. versionadded:: 0.19
       l1 penalty with SAGA solver (allowing 'multinomial' + L1)

dual : bool, default=False
    Dual or primal formulation. Dual formulation is only implemented for
    l2 penalty with liblinear solver. Prefer dual=False when
    n_samples > n_features.

tol : float, default=1e-4
    Tolerance for stopping criteria.

C : float, default=1.0
    Inverse of regularization strength; must be a positive float.
    Like in support vector machines, smaller values specify stronger
    regularization.

fit_intercept : bool, default=True
    Specifies if a constant (a.k.a. bias or intercept) should be
    added to the decision function.

intercept_scaling : float, default=1
    Useful only when the solver 'liblinear' is used
    and self.fit_intercept is set to True. In this case, x becomes
    [x, self.intercept_scaling],
    i.e. a "synthetic" feature with constant value equal to
    intercept_scaling is appended to the instance vector.
    The intercept becomes ``intercept_scaling * synthetic_feature_weight``.

    Note! the synthetic feature weight is subject to l1/l2 regularization
    as all other features.
    To lessen the effect of regularization on synthetic feature weight
    (and therefore on the intercept) intercept_scaling has to be increased.

class_weight : dict or 'balanced', default=None
    Weights associated with classes in the form ``{class_label: weight}``.
    If not given, all classes are supposed to have weight one.
```

```
    The "balanced" mode uses the values of y to automatically adjust
    weights inversely proportional to class frequencies in the input data
    as ``n_samples / (n_classes * np.bincount(y))``.

    Note that these weights will be multiplied with sample_weight (passed
    through the fit method) if sample_weight is specified.

    .. versionadded:: 0.17
       *class_weight='balanced'*

random_state : int, RandomState instance, default=None
    Used when ``solver`` == 'sag', 'saga' or 'liblinear' to shuffle the
    data. See :term:`Glossary <random_state>` for details.

solver : {'newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'},
 ↪default='lbfgs'

    Algorithm to use in the optimization problem. Default is 'lbfgs'.
    To choose a solver, you might want to consider the following aspects:

        - For small datasets, 'liblinear' is a good choice, whereas 'sag'
          and 'saga' are faster for large ones;
        - For multiclass problems, only 'newton-cg', 'sag', 'saga' and
          'lbfgs' handle multinomial loss;
        - 'liblinear' is limited to one-versus-rest schemes.

    .. warning::
       The choice of the algorithm depends on the penalty chosen:
       Supported penalties by solver:

       - 'newton-cg'   -   ['l2', 'none']
       - 'lbfgs'       -   ['l2', 'none']
       - 'liblinear'   -   ['l1', 'l2']
       - 'sag'         -   ['l2', 'none']
       - 'saga'        -   ['elasticnet', 'l1', 'l2', 'none']

    .. note::
       'sag' and 'saga' fast convergence is only guaranteed on
       features with approximately the same scale. You can
       preprocess the data with a scaler from :mod:`sklearn.preprocessing`.

    .. seealso::
       Refer to the User Guide for more information regarding
       :class:`LogisticRegression` and more specifically the
       `Table <https://scikit-learn.org/dev/modules/linear_model.
 ↪html#logistic-regression>`_
```

```
        summarazing solver/penalty supports.
        <!--
        # noqa: E501
        -->

    .. versionadded:: 0.17
       Stochastic Average Gradient descent solver.
    .. versionadded:: 0.19
       SAGA solver.
    .. versionchanged:: 0.22
        The default solver changed from 'liblinear' to 'lbfgs' in 0.22.

max_iter : int, default=100
    Maximum number of iterations taken for the solvers to converge.

multi_class : {'auto', 'ovr', 'multinomial'}, default='auto'
    If the option chosen is 'ovr', then a binary problem is fit for each
    label. For 'multinomial' the loss minimised is the multinomial loss fit
    across the entire probability distribution, *even when the data is
    binary*. 'multinomial' is unavailable when solver='liblinear'.
    'auto' selects 'ovr' if the data is binary, or if solver='liblinear',
    and otherwise selects 'multinomial'.

    .. versionadded:: 0.18
       Stochastic Average Gradient descent solver for 'multinomial' case.
    .. versionchanged:: 0.22
        Default changed from 'ovr' to 'auto' in 0.22.

verbose : int, default=0
    For the liblinear and lbfgs solvers set verbose to any positive
    number for verbosity.

warm_start : bool, default=False
    When set to True, reuse the solution of the previous call to fit as
    initialization, otherwise, just erase the previous solution.
    Useless for liblinear solver. See :term:`the Glossary <warm_start>`.

    .. versionadded:: 0.17
       *warm_start* to support *lbfgs*, *newton-cg*, *sag*, *saga* solvers.

n_jobs : int, default=None
    Number of CPU cores used when parallelizing over classes if
    multi_class='ovr'". This parameter is ignored when the ``solver`` is
    set to 'liblinear' regardless of whether 'multi_class' is specified or
    not. ``None`` means 1 unless in a :obj:`joblib.parallel_backend`
    context. ``-1`` means using all processors.
    See :term:`Glossary <n_jobs>` for more details.
```

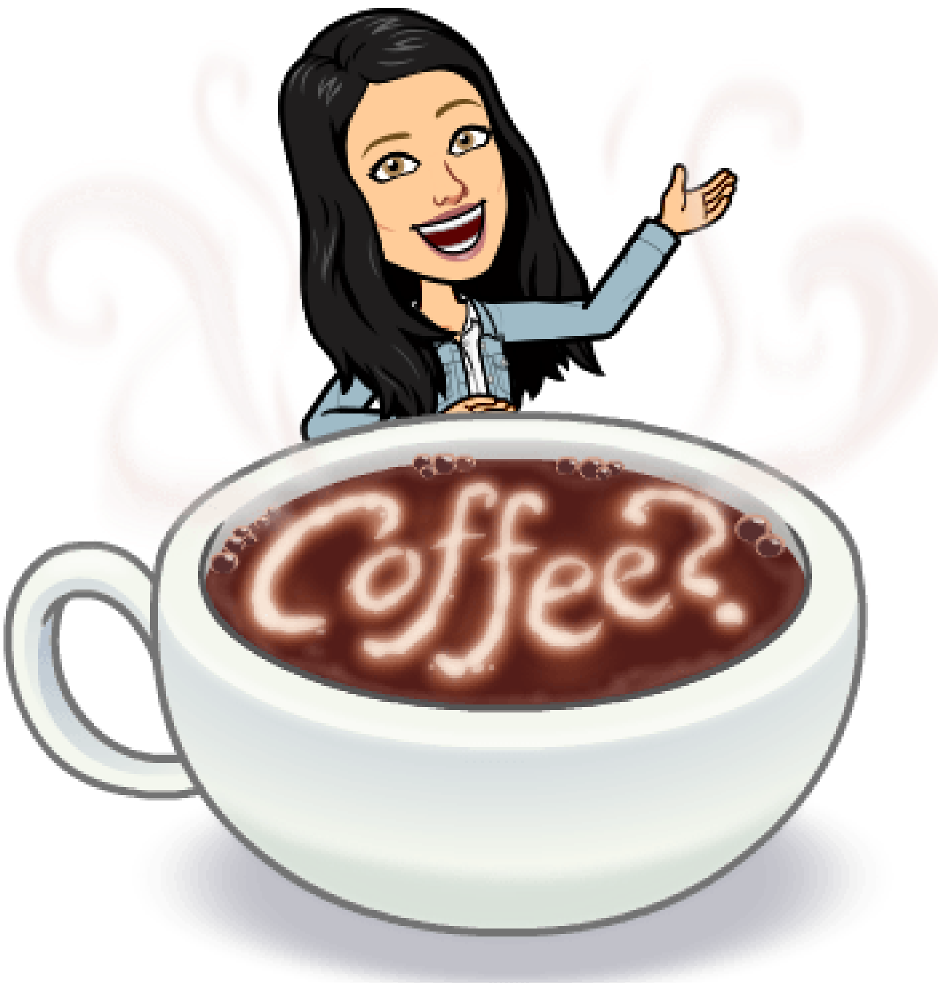
```
l1_ratio : float, default=None
    The Elastic-Net mixing parameter, with ``0 <= l1_ratio <= 1``. Only
    used if ``penalty='elasticnet'``. Setting ``l1_ratio=0`` is equivalent
    to using ``penalty='l2'``, while setting ``l1_ratio=1`` is equivalent
    to using ``penalty='l1'``. For ``0 < l1_ratio <1``, the penalty is a
    combination of L1 and L2.

Attributes
----------

classes_ : ndarray of shape (n_classes, )
    A list of class labels known to the classifier.

coef_ : ndarray of shape (1, n_features) or (n_classes, n_features)
    Coefficient of the features in the decision function.

    `coef_` is of shape (1, n_features) when the given problem is binary.
    In particular, when `multi_class='multinomial'`, `coef_` corresponds
    to outcome 1 (True) and `-coef_` corresponds to outcome 0 (False).

intercept_ : ndarray of shape (1,) or (n_classes,)
    Intercept (a.k.a. bias) added to the decision function.

    If `fit_intercept` is set to False, the intercept is set to zero.
    `intercept_` is of shape (1,) when the given problem is binary.
    In particular, when `multi_class='multinomial'`, `intercept_`
    corresponds to outcome 1 (True) and `-intercept_` corresponds to
    outcome 0 (False).

n_features_in_ : int
    Number of features seen during :term:`fit`.

    .. versionadded:: 0.24

feature_names_in_ : ndarray of shape (`n_features_in_`,)
    Names of features seen during :term:`fit`. Defined only when `X`
    has feature names that are all strings.

    .. versionadded:: 1.0

n_iter_ : ndarray of shape (n_classes,) or (1, )
    Actual number of iterations for all classes. If binary or multinomial,
    it returns only 1 element. For liblinear solver, only the maximum
    number of iteration across all classes is given.

    .. versionchanged:: 0.20

        In SciPy <= 1.0.0 the number of lbfgs iterations may exceed
```

```
        ``max_iter``. ``n_iter_`` will now report at most ``max_iter``.

See Also
--------
SGDClassifier : Incrementally trained logistic regression (when given
    the parameter ``loss="log"``).
LogisticRegressionCV : Logistic regression with built-in cross validation.

Notes
-----
The underlying C implementation uses a random number generator to
select features when fitting the model. It is thus not uncommon,
to have slightly different results for the same input data. If
that happens, try with a smaller tol parameter.

Predict output may not match that of standalone liblinear in certain
cases. See :ref:`differences from liblinear <liblinear_differences>`
in the narrative documentation.

References
----------

L-BFGS-B -- Software for Large-scale Bound-constrained Optimization
    Ciyou Zhu, Richard Byrd, Jorge Nocedal and Jose Luis Morales.
    http://users.iems.northwestern.edu/~nocedal/lbfgsb.html

LIBLINEAR -- A Library for Large Linear Classification
    https://www.csie.ntu.edu.tw/~cjlin/liblinear/

SAG -- Mark Schmidt, Nicolas Le Roux, and Francis Bach
    Minimizing Finite Sums with the Stochastic Average Gradient
    https://hal.inria.fr/hal-00860051/document

SAGA -- Defazio, A., Bach F. & Lacoste-Julien S. (2014).
    SAGA: A Fast Incremental Gradient Method With Support
    for Non-Strongly Convex Composite Objectives
    https://arxiv.org/abs/1407.0202

Hsiang-Fu Yu, Fang-Lan Huang, Chih-Jen Lin (2011). Dual coordinate descent
    methods for logistic regression and maximum entropy models.
    Machine Learning 85(1-2):41-75.
    https://www.csie.ntu.edu.tw/~cjlin/papers/maxent_dual.pdf

Examples
--------
>>> from sklearn.datasets import load_iris
>>> from sklearn.linear_model import LogisticRegression
>>> X, y = load_iris(return_X_y=True)
```

```
>>> clf = LogisticRegression(random_state=0).fit(X, y)
>>> clf.predict(X[:2, :])
array([0, 0])
>>> clf.predict_proba(X[:2, :])
array([[9.8...e-01, 1.8...e-02, 1.4...e-08],
       [9.7...e-01, 2.8...e-02, ...e-08]])
>>> clf.score(X, y)
0.97...
File:           ~/miniconda3/envs/cpsc330/lib/python3.10/site-packages/sklearn/
 ↪linear_model/_logistic.py
Type:           type
Subclasses:     LogisticRegressionCV
```

- We can see that there's a `multi_class` parameter, that can be set to `'ovr'` or `'multinomial'`, or you can have it automatically choose between the two, which is the default.
  - In CPSC 340 we discuss in detail the difference between these two approaches.
  - In CPSC 340 we make an argument for preferring `'multinomial'`, but in short it doesn't matter which one you choose.

1.5 Break (5 min)



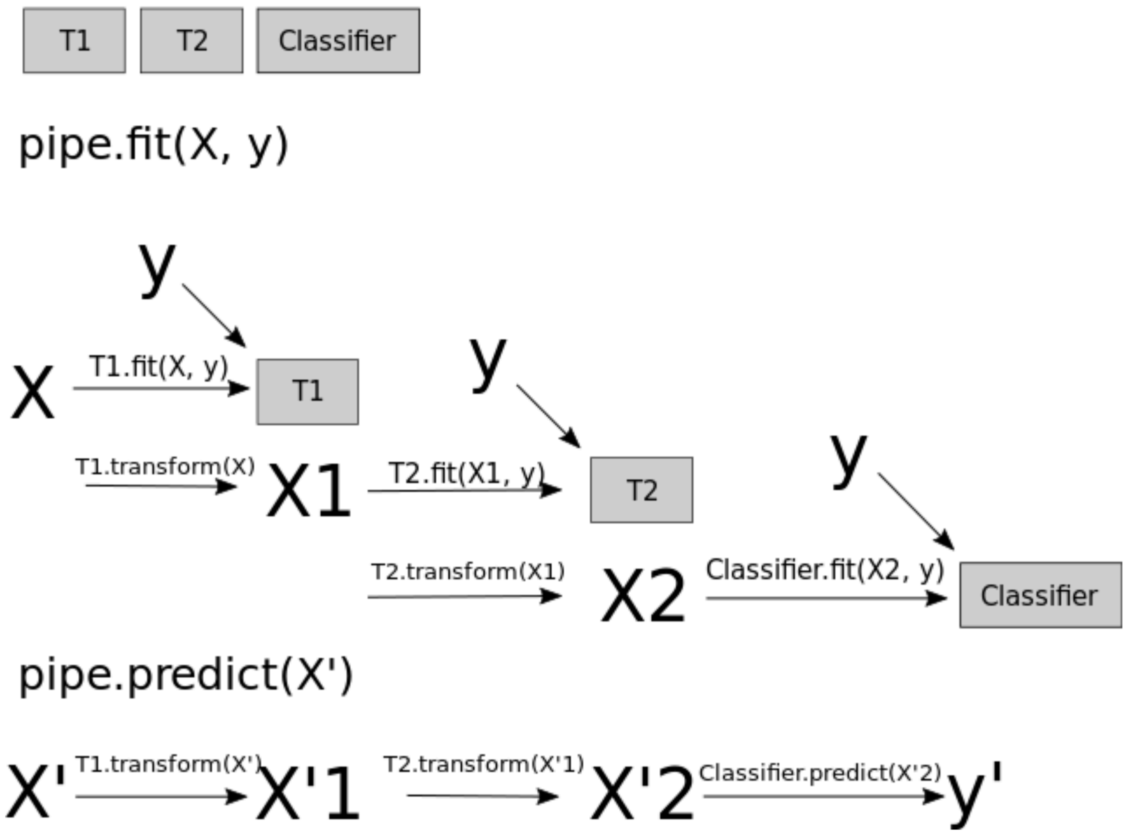
1.6 Intro to computer vision

- Computer vision refers to understanding images/videos, usually using ML/AI.
- Computer vision has many tasks of interest:
  - image classification: is this a cat or a dog?
  - object localization: where are the people in this image?
  - image segmentation: what are the various parts of this image?
  - motion detection: what moved between frames of a video?
  - and much more…
- We will focus on image classification.

1.7 Intro to neural networks

- Very popular these days thanks to **deep learning**.
- Neural networks apply a sequence of transformations on your input data.
- At a very high level you can think of them as `Pipelines` in `sklearn`.

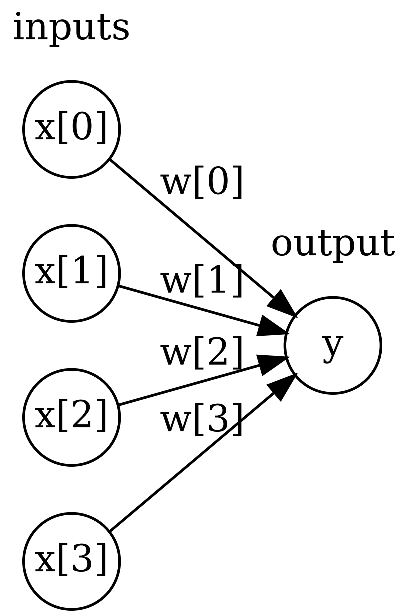
- A neural network is a model that's sort of like its own pipeline
  - It involves a series of transformations ("layers") internally.
  - The output is the prediction.



Source

- They can be viewed a **generalization of linear models** where we apply a series of transformations.
- Here is graphical representation of logistic regression model.
  - We have 4 features: x[0], x[1], x[2], x[3]

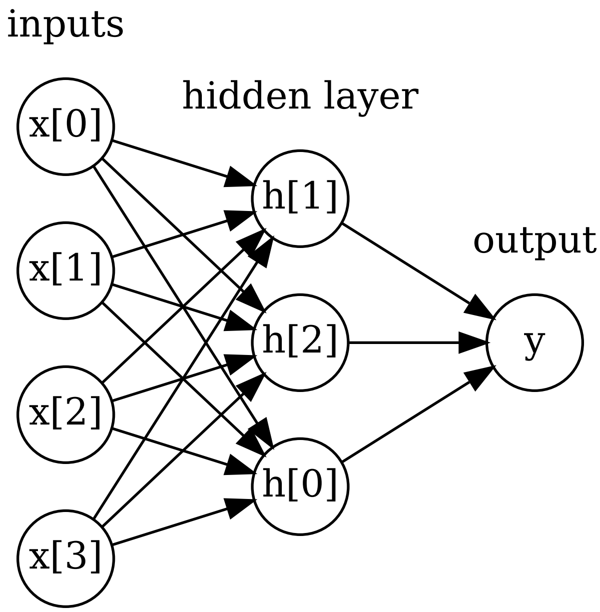
[33]:
```
import mglearn

display(mglearn.plots.plot_logistic_regression_graph())
```



- Below we are adding one "layer" of transformations in between features and the target.
- We are repeating the the process of computing the weighted sum multiple times.

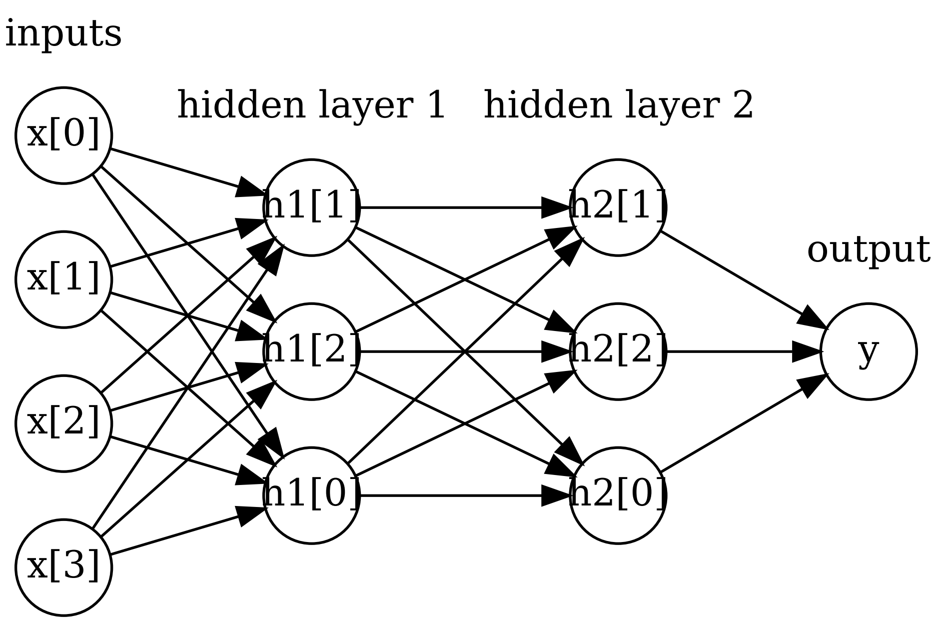
- The **hidden units** (e.g., h[1], h[2], …) represent the intermediate processing steps.

[34]:
```
display(mglearn.plots.plot_single_hidden_layer_graph())
```



- Now we are adding one more layer of transformations.

[35]:
```
display(mglearn.plots.plot_two_hidden_layer_graph())
```



- Important question: how many features before/after transformation.
  - e.g. scaling doesn't change the number of features
  - OHE increases the number of features
- With a neural net, you specify the number of features after each transformation.
  - In the above, it goes from 4 to 3 to 3 to 1.
- To make them really powerful compared to the linear models, we apply a non-linear function to the weighted sum for each hidden node.

1.7.1 Terminology

- Neural network = neural net
- Deep learning ~ using neural networks

1.7.2 Why neural networks?

- They can learn very complex functions.
  - The fundamental tradeoff is primarily controlled by the **number of layers** and **layer sizes**.
  - More layers / bigger layers –> more complex model.
  - You can generally get a model that will not underfit.

1.7.3 Why neural networks?

- They work really well for structured data:
  - 1D sequence, e.g. timeseries, language
  - 2D image
  - 3D image or video
- They've had some incredible successes in the last 10 years.
- Transfer learning (coming later today) is really useful.

1.7.4 Why not neural networks?

- Often they require a lot of data.
- They require a lot of compute time, and, to be faster, specialized hardware called GPUs.
- They have huge numbers of hyperparameters, which are a huge pain to tune.
  - Think of each layer having hyperparameters, plus some overall hyperparameters.
  - Being slow compounds this problem.
- They are not interpretable.

1.7.5 Why not neural networks?

- When you call `fit`, you are not guaranteed to get the optimal.
  - There are now a bunch of hyperparameters specific to `fit`, rather than the model.
  - You never really know if `fit` was successful or not.
  - You never really know if you should have run `fit` for longer.
- I don't recommend training them on your own without further training
  - Take CPSC 340 and other courses if you're interested.

- I'll show you some ways to use neural networks **without calling `fit`**.

1.7.6 Deep learning software

- scikit-learn has MLPRegressor and MLPClassifier but they aren't very flexible.
  - In general you'll want to leave the scikit-learn ecosystem when using neural networks.
  - Fun fact: these classes were contributed to scikit-learn by a UBC graduate student.
- There's been a lot of deep learning software out there.
- The current big players are:

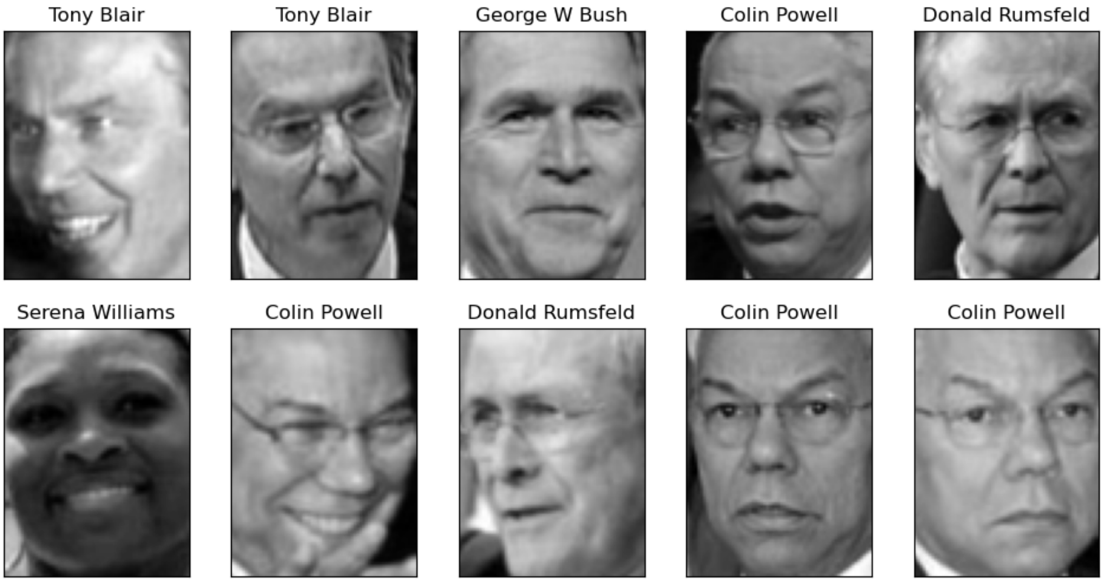
1. TensorFlow
2. PyTorch

- Both are heavily used in industry.
- If interested, see comparison of deep learning software.

1.8 Neural networks on image data

[36]:
```
import matplotlib as mpl
from sklearn.datasets import fetch_lfw_people

mpl.rcParams.update(mpl.rcParamsDefault)
plt.rcParams["image.cmap"] = "gray"
```

[37]:
```
from sklearn.datasets import fetch_lfw_people

people = fetch_lfw_people(min_faces_per_person=40, resize=0.7)

fig, axes = plt.subplots(2, 5, figsize=(12, 6), subplot_kw={"xticks": (),␣
 ↪"yticks": ()})
for target, image, ax in zip(people.target, people.images, axes.ravel()):
    ax.imshow(image)
    ax.set_title(people.target_names[target])
```



[38]:
```python
image_shape = people.images[0].shape
print("people.images.shape: {}".format(people.images.shape))
print("people.data.shape: {}".format(people.data.shape))
print("Number of classes: {}".format(len(people.target_names)))
```

```
people.images.shape: (1867, 87, 65)
people.data.shape: (1867, 5655)
Number of classes: 19
```

There are 1,560 images stored as arrays of 5655 pixels (87 by 65), of 19 different people:

[39]:
```python
# count how often each target appears
counts = np.bincount(people.target)
df = pd.DataFrame(counts, columns=["count"], index=people.target_names)
df.sort_values("count", ascending=False)
```

[39]:

	count
George W Bush	530
Colin Powell	236
Tony Blair	144
Donald Rumsfeld	121
Gerhard Schroeder	109
Ariel Sharon	77
Hugo Chavez	71
Junichiro Koizumi	60
Jean Chretien	55
John Ashcroft	53
Jacques Chirac	52

```
Serena Williams             52
Vladimir Putin              49
Luiz Inacio Lula da Silva   48
Gloria Macapagal Arroyo     44
Arnold Schwarzenegger       42
Jennifer Capriati           42
Laura Bush                  41
Lleyton Hewitt              41
```

Let's make the data less skewed by taking only 20 images of each person.

[40]:
```
people.target.shape
```

[40]:
```
(1867,)
```

[41]:
```
mask = np.zeros(people.target.shape, dtype=bool)
for target in np.unique(people.target):
    mask[np.where(people.target == target)[0][:20]] = 1

X_people = people.data[mask]
y_people = people.target[mask]
```

[42]:
```
X_people.shape, people.data.shape, y_people.shape, people.target.shape
```

[42]:
```
((380, 5655), (1867, 5655), (380,), (1867,))
```

[43]:
```
20*19, 87*65  # 20 images of 19 people, each having 5655 pixels
```

[43]:
```
(380, 5655)
```

[44]:
```
# scale the grayscale values to be between 0 and 1
# instead of 0 and 255 for better numeric stability
X_people = X_people / 255.0
```

[45]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X_people, y_people, random_state=123
)
```

[46]:
```
X_train
```

[46]:
```
array([[0.8156863 , 0.80653596, 0.7908497 , …, 0.751634  , 0.87058824,
        0.8366013 ],
       [0.13725491, 0.13464051, 0.13202615, …, 0.21045752, 0.20915033,
        0.20653595],
       [0.44183007, 0.49019608, 0.5555556 , …, 0.9843137 , 0.98169935,
        0.9764706 ],
       …,
       [0.8352941 , 0.8405229 , 0.8392157 , …, 0.66928107, 0.4248366 ,
```

```
 0.47843137],
[0.6261438 , 0.6562091 , 0.654902  , …, 0.11895425, 0.1254902 ,
 0.13986929],
[0.16470589, 0.16601306, 0.16601306, …, 0.6326797 , 0.6183007 ,
 0.60130715]], dtype=float32)
```

Now the data is in this tabular format that we are used to. Now we can use our usual classification methods.

[47]:
```
lr = LogisticRegression(max_iter=4000)
lr.fit(X_train, y_train);
```

[48]:
```
lr.score(X_train, y_train)
```

[48]:
```
1.0
```

[49]:
```
lr.score(X_test, y_test)
```

[49]:
```
0.4842105263157895
```

We are getting very poor test results :(

- Why flattening images is a bad idea?
  - By "flattening" the image we throw away useful information.
- What the computer sees for each image:

[50]:
```
X_train[0]
```

[50]:
```
array([0.8156863 , 0.80653596, 0.7908497 , …, 0.751634  , 0.87058824,
       0.8366013 ], dtype=float32)
```

- Hard to classify this!
- Convolutional neural networks (CNNs) can take in images without flattening them.
  - We won't cover CNNs here, but they are in CPSC 340.

1.9 Transfer learning

- In practice, very few people train an entire CNN from scratch because it requires a large dataset, powerful computers, and a huge amount of human effort to train the model.
- Instead, a common practice is to download a pre-trained model and fine tune it for your task.

- This is called **transfer learning**.
- Transfer learning is one of the most common techniques used in the context of computer vision and natural language processing.
  - In the last lecture we used pre-trained embeddings to train create text representation.

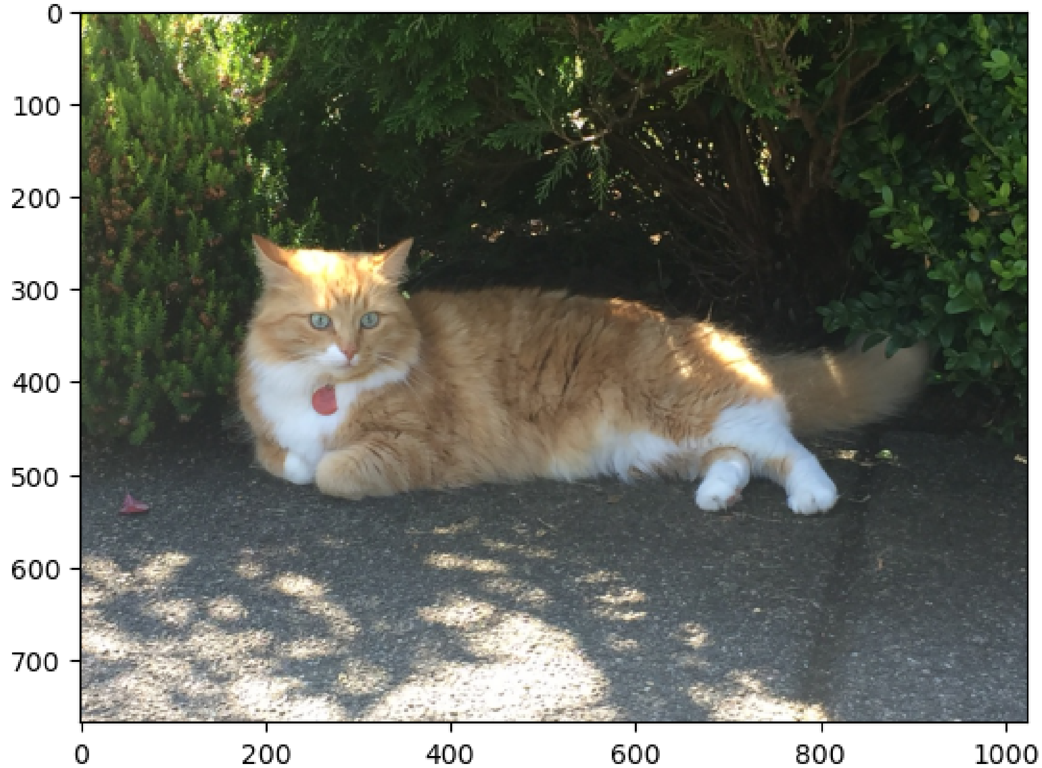
1.9.1 Using pre-trained models out-of-the-box

Recall this example from a while back:

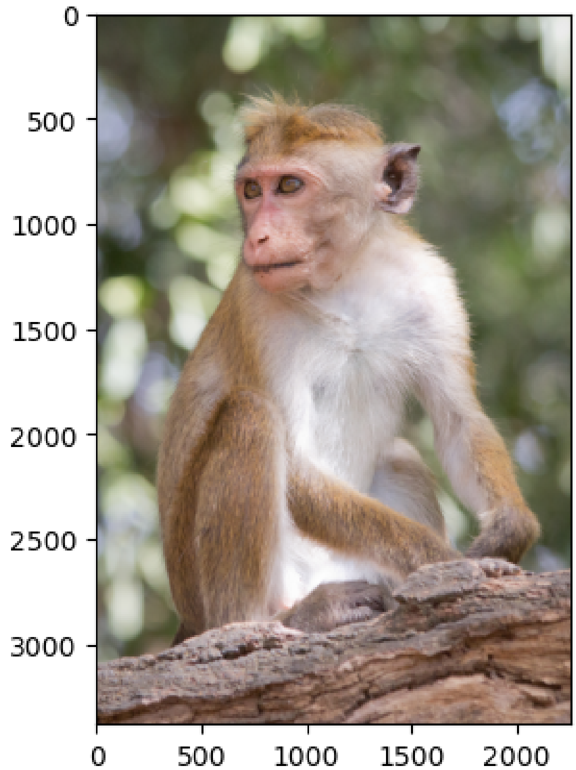
[51]:
```
import torch
from PIL import Image
from torchvision import transforms
from torchvision.models import vgg16
```

[52]:
```
def classify_image(img, topn=4):
    clf = vgg16(pretrained=True)  # Loading the pre-trained model
    preprocess = transforms.Compose(
        [
            transforms.Resize(299),
            transforms.CenterCrop(299),
            transforms.ToTensor(),
            transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224,␣
 ↪0.225]),
        ]
    )  # Defining a preprocessor to transform a given image so that it's␣
 ↪suitable to to pass for prediction

    with open("data/imagenet_classes.txt") as f:
        classes = [line.strip() for line in f.readlines()]

    img_t = preprocess(img)
    batch_t = torch.unsqueeze(img_t, 0)
    clf.eval()
    output = clf(batch_t)
    _, indices = torch.sort(output, descending=True)
    probabilities = torch.nn.functional.softmax(output, dim=1)
    d = {
        "Class": [classes[idx] for idx in indices[0][:topn]],
        "Probability score": [
            np.round(probabilities[0, idx].item(), 3) for idx in indices[0][:
 ↪topn]
        ],
    }
    df = pd.DataFrame(d, columns=["Class", "Probability score"])
    return df
```

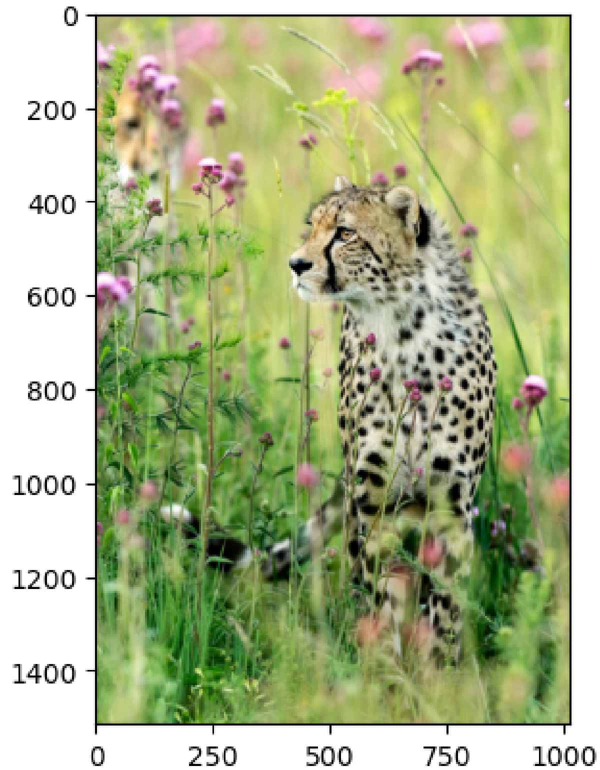
[53]:
```
# Predict labels with associated probabilities for unseen images
images = glob.glob("data/test_images/*.*")
for image in images:
    img = Image.open(image)
    img.load()
    plt.imshow(img)
    plt.show()
    df = classify_image(img)
    print(df.to_string(index=False))
    print("--------------------------------------------------------------")
```



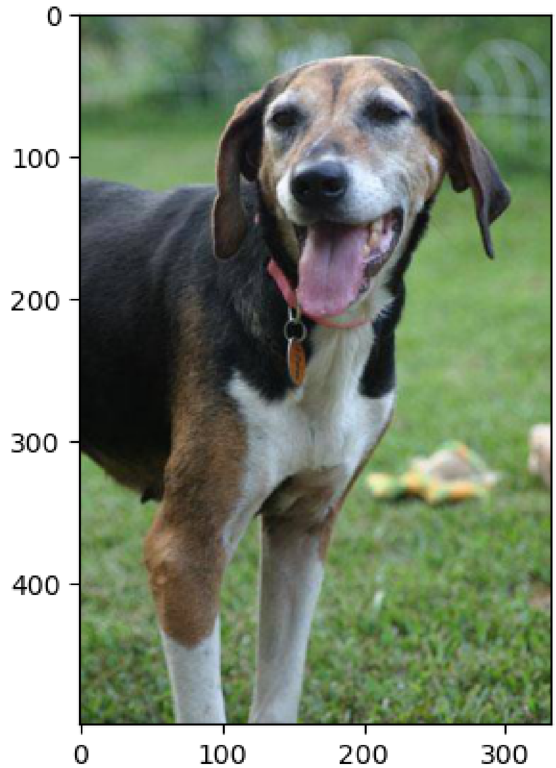

```
                     Class  Probability score
                 tiger cat              0.357
          tabby, tabby cat              0.207
           lynx, catamount              0.049
Pembroke, Pembroke Welsh corgi          0.046
--------------------------------------------------------------
```



Class	Probability score
macaque	0.714
patas, hussar monkey, Erythrocebus patas	0.122
proboscis monkey, Nasalis larvatus	0.098
guenon, guenon monkey	0.017




```
                                 Class  Probability score
         cheetah, chetah, Acinonyx jubatus              0.982
                  leopard, Panthera pardus              0.012
jaguar, panther, Panthera onca, Felis onca              0.004
       snow leopard, ounce, Panthera uncia              0.001
-------------------------------------------------------------
```




```
                       Class  Probability score
Walker hound, Walker foxhound              0.577
                 EntleBucher              0.089
             English foxhound              0.086
                      beagle              0.063
--------------------------------------------------------------
```

- We got these predictions without "doing the ML ourselves".
- We are using **pre-trained** `vgg16` model which is available in `torchvision`
- `torchvision` has many such pre-trained models available that have been very successful across a wide range of tasks: AlexNet, VGG, ResNet, Inception, MobileNet, etc.
- Many of these models have been pre-trained on famous datasets like **ImageNet**.

1.9.2 ImageNet

- ImageNet is an image dataset that became a very popular benchmark in the field ~10 years ago.
- Wikipedia article
- There are 14 million images and 1000 classes.
- Here are some example classes.

[54]:
```
with open("data/imagenet_classes.txt") as f:
    classes = [line.strip() for line in f.readlines()]
```

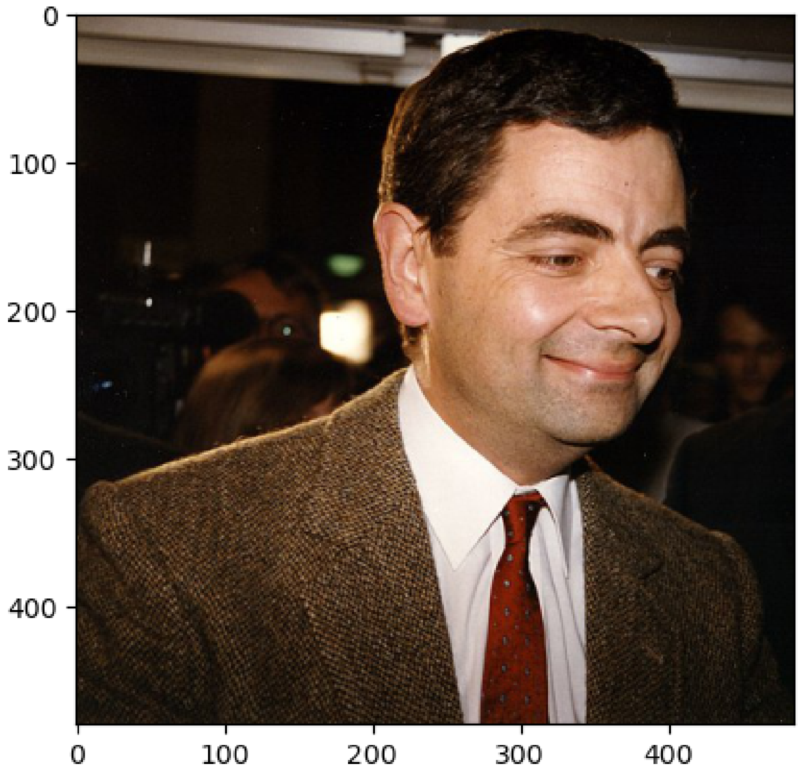
```
classes[100:110]
```

[54]:
```
['black swan, Cygnus atratus',
 'tusker',
 'echidna, spiny anteater, anteater',
 'platypus, duckbill, duckbilled platypus, duck-billed platypus, Ornithorhynchus
anatinus',
 'wallaby, brush kangaroo',
 'koala, koala bear, kangaroo bear, native bear, Phascolarctos cinereus',
 'wombat',
 'jellyfish',
 'sea anemone, anemone',
 'brain coral']
```

Let's see what labels this pre-trained model give us for some unlabeled pictures. Try it with your own pictures!

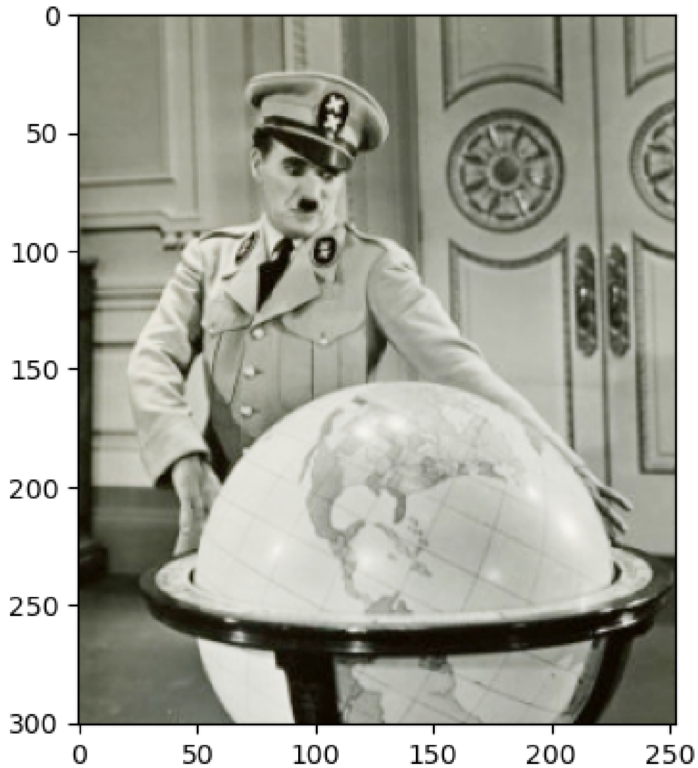
Images Sources: - https://en.wikipedia.org/wiki/Charlie_Chaplin - https://en.wikipedia.org/wiki/Mr._Bean

[55]:
```
# Predict labels with associated probabilities for unseen images
images = glob.glob("data/some_people/*.*")
for image in images:
    img = Image.open(image)
    img.load()
    plt.imshow(img)
    plt.show()
    df = classify_image(img)
    print(df.to_string(index=False))
    print("--------------------------------------------------------------")
```




```
                  Class  Probability score
   suit, suit of clothes             0.417
             Windsor tie             0.253
bow tie, bow-tie, bowtie             0.214
       groom, bridegroom             0.049
--------------------------------------------------------------
```

Class	Probability score
wig	0.273
fur coat	0.126
bonnet, poke bonnet	0.090
cloak	0.058




```
                Class  Probability score
hoopskirt, crinoline                0.277
            vestment                0.055
          steel drum                0.045
   groom, bridegroom                0.029
--------------------------------------------------------------
```

- It's not doing very well here because ImageNet don't have classes for Charlie Chaplin, Lita Grey, Rowan Atkinson.
- Here we are using pre-trained models out-of-the-box.
- Can we use pre-trained models for our own classification problem with our classes?
- Yes!!

1.10 Using pre-trained models as feature extractor

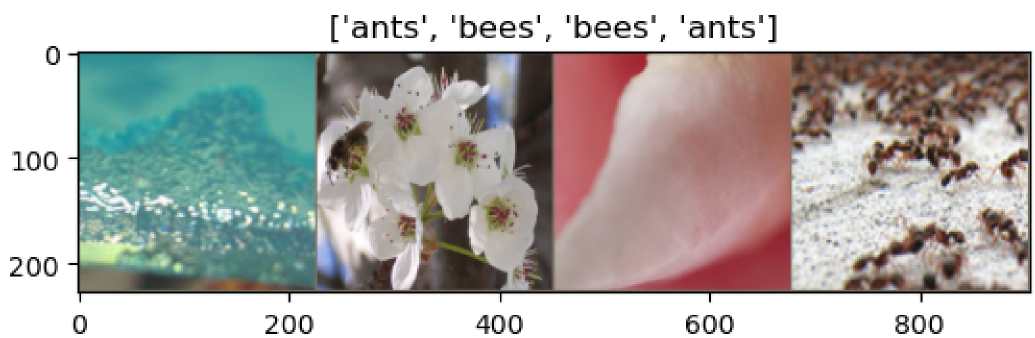
- Here we will use **pre-trained** models to **extract features**.
- We will pass our specific **data through a pre-trained** network to get a **feature vector** for each example in the data.
- You **train a machine learning classifier** such as logistic regression or random forest using these extracted feature vectors.

We will use the Hymenoptera Data from a transfer learning tutorial on PyTorch.org.

[56]:
```python
# Attribution: [Code from PyTorch docs](https://pytorch.org/tutorials/beginner/
↪transfer_learning_tutorial.html?highlight=transfer%20learning)

import copy
import os
import time

import matplotlib.pyplot as plt
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
from torch.optim import lr_scheduler
from torchvision import datasets, models, transforms

data_transforms = {
    "train": transforms.Compose(
        [
            transforms.RandomResizedCrop(224),
            transforms.RandomHorizontalFlip(),
            transforms.ToTensor(),
            transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225]),
        ]
    ),
    "val": transforms.Compose(
        [
            transforms.Resize(256),
            transforms.CenterCrop(224),
            transforms.ToTensor(),
            transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225]),
        ]
    ),
}
data_dir = "data/hymenoptera_data"
image_datasets = {
    x: datasets.ImageFolder(os.path.join(data_dir, x), data_transforms[x])
    for x in ["train", "val"]
}
dataloaders = {
    x: torch.utils.data.DataLoader(
        image_datasets[x], batch_size=4, shuffle=True, num_workers=4
    )
    for x in ["train", "val"]
}
dataset_sizes = {x: len(image_datasets[x]) for x in ["train", "val"]}
class_names = image_datasets["train"].classes
```

```python
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

[57]:
```python
def imshow(inp, title=None):
    """Imshow for Tensor."""
    inp = inp.numpy().transpose((1, 2, 0))
    mean = np.array([0.485, 0.456, 0.406])
    std = np.array([0.229, 0.224, 0.225])
    inp = std * inp + mean
    inp = np.clip(inp, 0, 1)
    plt.imshow(inp)
    if title is not None:
        plt.title(title)
    plt.pause(0.001)  # pause a bit so that plots are updated


# Get a batch of training data
inputs, classes = next(iter(dataloaders["train"]))

# Make a grid from batch
out = torchvision.utils.make_grid(inputs)

imshow(out, title=[class_names[x] for x in classes])
```



[58]:
```python
print(f"Classes: {image_datasets['train'].classes}")
print(
    f"Class count: {[image_datasets['train'].targets.count(i) for i in [0, 1]]}"
)
print(f"Samples:", len(image_datasets["train"]))
print(f"First sample: {image_datasets['train'].samples[0]}")
```

```
Classes: ['ants', 'bees']
Class count: [123, 121]
Samples: 244
```

```
First sample: ('data/hymenoptera_data/train/ants/0013035.jpg', 0)
```

`torch.cat` concatenates a given sequence:

[59]:
```
# Attribution: [Code adapted from PyTorch docs](https://pytorch.org/docs/stable/
↪generated/torch.cat.html)

x = torch.randn(2, 3)
print("\n", x)
print("\n", torch.cat((x, x, x), dim=0))
print("\n", torch.cat((x, x, x), dim=1))
```

```
 tensor([[-0.7062, -0.7539,  0.8162],
        [-1.3644,  0.7026, -1.4110]])

 tensor([[-0.7062, -0.7539,  0.8162],
        [-1.3644,  0.7026, -1.4110],
        [-0.7062, -0.7539,  0.8162],
        [-1.3644,  0.7026, -1.4110],
        [-0.7062, -0.7539,  0.8162],
        [-1.3644,  0.7026, -1.4110]])

 tensor([[-0.7062, -0.7539,  0.8162, -0.7062, -0.7539,  0.8162, -0.7062,
-0.7539,
          0.8162],
        [-1.3644,  0.7026, -1.4110, -1.3644,  0.7026, -1.4110, -1.3644,  0.7026,
         -1.4110]])
```

[60]:
```
def get_features(model, train_loader, valid_loader):
    """Extract output of squeezenet model"""

    with torch.no_grad():  # turn off computational graph stuff
        Z_train = torch.empty((0, 1024))  # Initialize empty tensors
        y_train = torch.empty((0))
        Z_valid = torch.empty((0, 1024))
        y_valid = torch.empty((0))
        for X, y in train_loader:
            Z_train = torch.cat((Z_train, model(X)), dim=0)
            y_train = torch.cat((y_train, y))
        for X, y in valid_loader:
            Z_valid = torch.cat((Z_valid, model(X)), dim=0)
            y_valid = torch.cat((y_valid, y))
    return Z_train.detach(), y_train.detach(), Z_valid.detach(), y_valid.
↪detach()
```

[61]:
```
densenet = models.densenet121(pretrained=True)
densenet.classifier = nn.Identity()  # remove that last "classification" layer
```

[62]:
```
Z_train, y_train, Z_valid, y_valid = get_features(
    densenet, dataloaders["train"], dataloaders["val"]
)
```

Now we have some extracted features.

[63]:
```
Z_train.shape
```

[63]:
```
torch.Size([244, 1024])
```

[64]:
```
from sklearn.pipeline import Pipeline, make_pipeline
from sklearn.preprocessing import StandardScaler

pipe = make_pipeline(StandardScaler(), LogisticRegression(max_iter=2000))
pipe.fit(Z_train, y_train)
pipe.score(Z_train, y_train)
```

[64]:
```
1.0
```

[65]:
```
pipe.score(Z_valid, y_valid)
```

[65]:
```
0.7777777777777778
```

- This is great accuracy for so little data (we only have 244 examples) and little effort!!!

1.10.1 TODO

- Compare this to accuracy with flattened images and logistic regression
- Try this out with the Faces dataset.

1.11 Random cool stuff

- Style transfer: given a "content image" and a "style image", create a new image with the content of one and the style of the other.
  - Here is the original paper from 2015, see Figure 2.
  - Here are more in this 2016 paper; see, e.g. Figures 1 and 7.
  - This has been done for video as well; see this video from 2016.
- Image captioning: Transfer learning with NLP and vision
- Colourization: see this 2016 project.
- Inceptionism: let the neural network "make things up"
  - 2015 article
  - "Deep dream" video from 2015.

1.12 Summary

- Multi-class classification refers to classification with >2 classes.
  - Most sklearn classifiers work out of the box.
  - With `LogisticRegression` the situation with the coefficients is a bit funky, we get 1 coefficient per feature per class.

- Flattening images throws away a lot of useful information (sort of like one-hot encoding on ordinal variable!).
- Neural networks are a flexible class of models.
  - They are hard to train - a lot more on that in CPSC 340.
  - They generally require leaving the sklearn ecosystem to tensorflow or pytorch.
  - They are particular powerful for structured input like images, videos, audio, etc.
- The good news is we can use pre-trained neural networks.
  - This saves us a huge amount of time/cost/effort/resources.
  - We can use these pre-trained networks directly or use them as feature transformers.
- My general recommendation: don't use deep learning unless there is good reason to.