Mud card questions

- **lots of concern about coding and the tools we use**
  - data science is coding-heavy, python and R are used most often
  - the tools we use (github and environments) are pretty standard in the industry
- **I think it maybe inaccurate to classifying the text or video as unstructured data since sometimes we may use features from texts that turn out to be structured like length of text or email classification.**
  - yes, you can convert unstructured data into structured data (e.g., bag-of-words in NLP)
  - usually such conversions don't produce accurate ML models
- **I find it quite hard to divide supervised and unsupervised ML, because I find out that there are many supervised models using features come from unsupervised models. So the distinction between these two models may have gradually been vague as far as I think.**
  - if your goal is to predict a target variable, that's supervised ML regardless of what features you use.
  - unsupervised ML has no target variable to predict
- **"I am still not very clear about unsupervised learning. Could you spend some minutes on explaining that again?**
  - unsupervised ML means that you do not have a target variable y, you only work with a feature matrix X
- **I find the concept of reinforcement learning kind of difficult to understand.**
  - that's OK, we won't cover it in class :)
  - if you are interested in this topic, feel free to read more about it
- **For the projects, is it possible to see those/good homework examples from the previous students?**
  - Yes! I added two reports from last year to the github repo as an example
- **How do you make sense of a feature matrix and how do you know exactly which features to extract and which features to ignore to get the best understanding of the dataset?**
  - We will learn how to measure the importance of features
- **can Introduce the relationship and difference between machine learning and deep learning, such as is deep learning more powerful than ML? or they just be specialist in different fields!**
  - deep learning is a sub-field of ML, it uses neural networks
  - deep learning tends to be more powerful when applied to large datasets or when the dataset is unstructured

DATA1030: Hands-on Data Science

Intro to ML

Learning objectives

By the end of the lecture, you will be able to

- describe the main goals of the ML pipeline
- list the main steps of the ML pipeline
- explain the bias-variance trade off

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The supervised ML pipeline

The goals:

- use the training data (X and y) to develop a model which can accurately predict the target variable (y_new') for previously unseen data (X_new)
  - your model is a ML model
  - model performance or 'accuracy' is a metric you need to choose to measure model performance and objectively compare various models
- measure the generalization error: measure how well the model is expected to perform on previously unseen data

Learning objectives

By the end of the lecture, you will be able to

- describe the main goals of the ML pipeline
- **list the main steps of the ML pipeline**
- explain the bias-variance trade off

The steps

1. Exploratory Data Analysis (EDA): you need to understand your data and verify that it doesn't contain errors

- do as much EDA as you can!

2. Split the data into different sets: most often the sets are train, validation, and test (or holdout)

- practitioners often make errors in this step!
- you can split the data randomly, based on groups, based on time, or any other non-standard way if necessary to answer your ML question

3. Preprocess the data: ML models only work if X and Y are numbers! Some ML models additionally require each feature to have 0 mean and 1 standard deviation (standardized features)

- often the original features you get contain strings (for example a gender feature would contain 'male', 'female', 'non-binary', 'unknown') which needs to transformed into numbers
- often the features are not standardized (e.g., age is between 0 and 100) but it needs to be standardized

4. Choose an evaluation metric: depends on the priorities of the stakeholders

- often requires quite a bit of thinking and ethical considerations

5. Choose one or more ML techniques: it is highly recommended that you try multiple models

- start with simple models like linear or logistic regression
- try also more complex models like nearest neighbors, support vector machines, random forest, etc.

6. Tune the hyperparameters of your ML models (aka cross-validation)

- ML techniques have hyperparameters that you need to optimize to achieve best performance
- for each ML model, decide which parameters to tune and what values to try
- loop through each parameter combination
  - train one model for each parameter combination
  - evaluate how well the model performs on the validation set
- take the parameter combo that gives the best validation score
- evaluate that model on the test set to report how well the model is expected to perform on previously unseen data

7. Interpret your model: black boxes are often not useful

- check if your model uses features that make sense (excellent tool for debugging)
- often model predictions are not enough, you need to be able to explain how the model arrived to a particular prediction (e.g., in health care)

Quiz

Learning objectives

By the end of the lecture, you will be able to

- describe the main goals of the ML pipeline
- list the main steps of the ML pipeline
- **explain the bias-variance trade off**

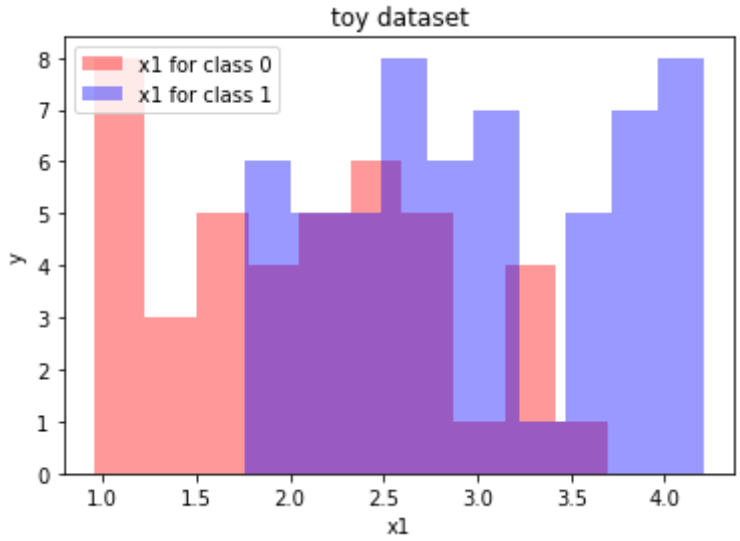
Bias-variance tradeoff illustrated through a simple ML pipeline

In [1]:
```
# import packages

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
from sklearn.svm import SVC
from matplotlib import pylab as plt
import matplotlib
from matplotlib.colors import ListedColormap
%matplotlib inline

# scikit-learn code is reproducable is the random seed is fixed.
np.random.seed(2)

# read in the data
# our toy dataset, we don't know how it was generated.
df = pd.read_csv('data/toy_data.csv')

X = df[['x1','x2']].values
y = df['y'].values

print(np.shape(X))
print(np.shape(y))
print(np.unique(y,return_counts=True))
```

```
(100, 2)
(100,)
(array([0, 1]), array([42, 58]))
```

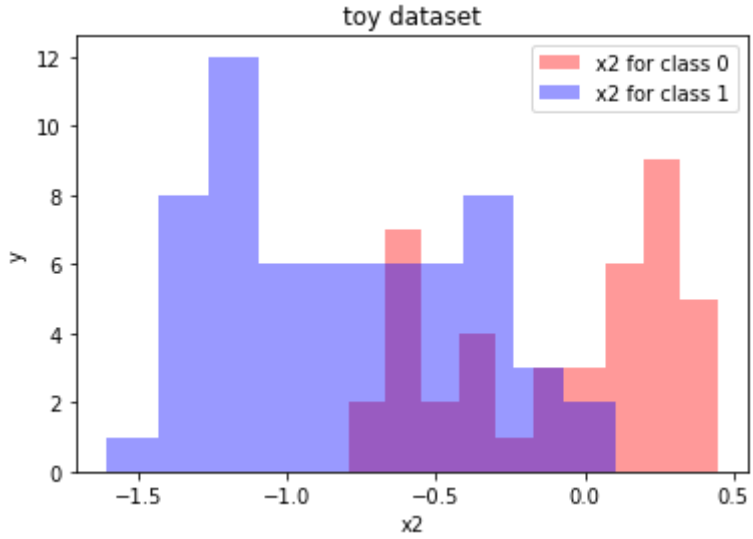
1. Exploratory Data Analysis (EDA)

In [2]:
```
plt.hist(X[y==0,0],alpha=0.4,color='r',label='x1 for class 0')
plt.hist(X[y==1,0],alpha=0.4,color='b',label='x1 for class 1')
plt.xlabel('x1')
plt.ylabel('y')
plt.title('toy dataset')
plt.legend()
plt.show()
```



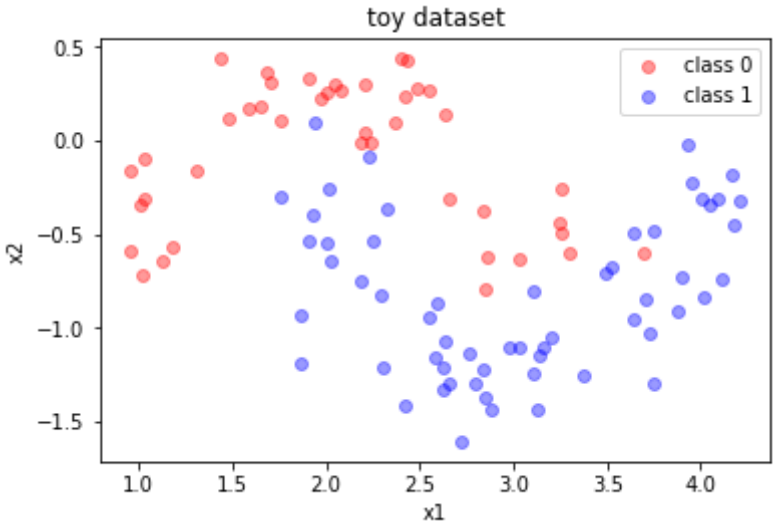
In [3]:

```
plt.hist(X[y==0,1],alpha=0.4,color='r',label='x2 for class 0')
plt.hist(X[y==1,1],alpha=0.4,color='b',label='x2 for class 1')
plt.xlabel('x2')
plt.ylabel('y')
plt.title('toy dataset')
plt.legend()
plt.show()
```



In [4]:

```
plt.scatter(X[y==0,0],X[y==0,1],color='r',label='class 0',alpha=0.4)
plt.scatter(X[y==1,0],X[y==1,1],color='b',label='class 1',alpha=0.4)
plt.xlabel('x1')
plt.ylabel('x2')
plt.title('toy dataset')
plt.gca().set_aspect('equal')
plt.legend()
plt.show()
```



2. Split the data into different sets

In [5]:
```
help(train_test_split)
```

```
Help on function train_test_split in module sklearn.model_selection._split:

train_test_split(*arrays, test_size=None, train_size=None, random_state=None, sh
uffle=True, stratify=None)
    Split arrays or matrices into random train and test subsets

    Quick utility that wraps input validation and
    ``next(ShuffleSplit().split(X, y))`` and application to input data
    into a single call for splitting (and optionally subsampling) data in a
    oneliner.

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

    Parameters
    ----------
    *arrays : sequence of indexables with same length / shape[0]
        Allowed inputs are lists, numpy arrays, scipy-sparse
        matrices or pandas dataframes.

    test_size : float or int, default=None
        If float, should be between 0.0 and 1.0 and represent the proportion
        of the dataset to include in the test split. If int, represents the
        absolute number of test samples. If None, the value is set to the
        complement of the train size. If ``train_size`` is also None, it will
        be set to 0.25.

    train_size : float or int, default=None
        If float, should be between 0.0 and 1.0 and represent the
        proportion of the dataset to include in the train split. If
        int, represents the absolute number of train samples. If None,
        the value is automatically set to the complement of the test size.

    random_state : int, RandomState instance or None, default=None
        Controls the shuffling applied to the data before applying the split.
        Pass an int for reproducible output across multiple function calls.
        See :term:`Glossary <random_state>`.
```

```
    shuffle : bool, default=True
        Whether or not to shuffle the data before splitting. If shuffle=False
        then stratify must be None.

    stratify : array-like, default=None
        If not None, data is split in a stratified fashion, using this as
        the class labels.
        Read more in the :ref:`User Guide <stratification>`.

    Returns
    -------
    splitting : list, length=2 * len(arrays)
        List containing train-test split of inputs.

        .. versionadded:: 0.16
            If the input is sparse, the output will be a
            ``scipy.sparse.csr_matrix``. Else, output type is the same as the
            input type.

    Examples
    --------
    >>> import numpy as np
    >>> from sklearn.model_selection import train_test_split
    >>> X, y = np.arange(10).reshape((5, 2)), range(5)
    >>> X
    array([[0, 1],
           [2, 3],
           [4, 5],
           [6, 7],
           [8, 9]])
    >>> list(y)
    [0, 1, 2, 3, 4]

    >>> X_train, X_test, y_train, y_test = train_test_split(
    ...     X, y, test_size=0.33, random_state=42)
    ...
    >>> X_train
    array([[4, 5],
           [0, 1],
           [6, 7]])
    >>> y_train
    [2, 0, 3]
    >>> X_test
    array([[2, 3],
           [8, 9]])
    >>> y_test
    [1, 4]

    >>> train_test_split(y, shuffle=False)
    [[0, 1, 2], [3, 4]]
```

In [6]:

```
X_train, X_other, y_train, y_other = train_test_split(X,y,test_size=0.4)
print(np.shape(X_other),np.shape(y_other))
print('train:',np.shape(X_train),np.shape(y_train))

X_val, X_test, y_val, y_test = train_test_split(X_other,y_other,test_size=0.5)
print('val:',np.shape(X_val),np.shape(y_val))
print('test:',np.shape(X_test),np.shape(y_test))
```

```
(40, 2) (40,)
train: (60, 2) (60,)
val: (20, 2) (20,)
test: (20, 2) (20,)
```

3. Preprocess the data

In [7]:

```
help(StandardScaler)
```

```
Help on class StandardScaler in module sklearn.preprocessing._data:

class StandardScaler(sklearn.base.TransformerMixin, sklearn.base.BaseEstimator)
 |  StandardScaler(*, copy=True, with_mean=True, with_std=True)
 |
 |  Standardize features by removing the mean and scaling to unit variance
 |
 |  The standard score of a sample `x` is calculated as:
 |
 |      z = (x - u) / s
 |
 |  where `u` is the mean of the training samples or zero if `with_mean=False`,
 |  and `s` is the standard deviation of the training samples or one if
 |  `with_std=False`.
 |
 |  Centering and scaling happen independently on each feature by computing
 |  the relevant statistics on the samples in the training set. Mean and
 |  standard deviation are then stored to be used on later data using
 |  :meth:`transform`.
 |
 |  Standardization of a dataset is a common requirement for many
 |  machine learning estimators: they might behave badly if the
 |  individual features do not more or less look like standard normally
 |  distributed data (e.g. Gaussian with 0 mean and unit variance).
 |
 |  For instance many elements used in the objective function of
 |  a learning algorithm (such as the RBF kernel of Support Vector
 |  Machines or the L1 and L2 regularizers of linear models) assume that
 |  all features are centered around 0 and have variance in the same
 |  order. If a feature has a variance that is orders of magnitude larger
 |  that others, it might dominate the objective function and make the
 |  estimator unable to learn from other features correctly as expected.
 |
 |  This scaler can also be applied to sparse CSR or CSC matrices by passing
 |  `with_mean=False` to avoid breaking the sparsity structure of the data.
 |
 |  Read more in the :ref:`User Guide <preprocessing_scaler>`.
 |
 |  Parameters
 |  ----------
 |  copy : bool, default=True
 |      If False, try to avoid a copy and do inplace scaling instead.
 |      This is not guaranteed to always work inplace; e.g. if the data is
 |      not a NumPy array or scipy.sparse CSR matrix, a copy may still be
 |      returned.
 |
 |  with_mean : bool, default=True
 |      If True, center the data before scaling.
 |      This does not work (and will raise an exception) when attempted on
 |      sparse matrices, because centering them entails building a dense
 |      matrix which in common use cases is likely to be too large to fit in
```

```
    memory.

with_std : bool, default=True
    If True, scale the data to unit variance (or equivalently,
    unit standard deviation).

Attributes
----------
scale_ : ndarray of shape (n_features,) or None
    Per feature relative scaling of the data to achieve zero mean and unit
    variance. Generally this is calculated using `np.sqrt(var_)`. If a
    variance is zero, we can't achieve unit variance, and the data is left
    as-is, giving a scaling factor of 1. `scale_` is equal to `None`
    when `with_std=False`.

    .. versionadded:: 0.17
       *scale_*

mean_ : ndarray of shape (n_features,) or None
    The mean value for each feature in the training set.
    Equal to ``None`` when ``with_mean=False``.

var_ : ndarray of shape (n_features,) or None
    The variance for each feature in the training set. Used to compute
    `scale_`. Equal to ``None`` when ``with_std=False``.

n_samples_seen_ : int or ndarray of shape (n_features,)
    The number of samples processed by the estimator for each feature.
    If there are no missing samples, the ``n_samples_seen`` will be an
    integer, otherwise it will be an array of dtype int. If
    `sample_weights` are used it will be a float (if no missing data)
    or an array of dtype float that sums the weights seen so far.
    Will be reset on new calls to fit, but increments across
    ``partial_fit`` calls.

Examples
--------
>>> from sklearn.preprocessing import StandardScaler
>>> data = [[0, 0], [0, 0], [1, 1], [1, 1]]
>>> scaler = StandardScaler()
>>> print(scaler.fit(data))
StandardScaler()
>>> print(scaler.mean_)
[0.5 0.5]
>>> print(scaler.transform(data))
[[-1. -1.]
 [-1. -1.]
 [ 1.  1.]
 [ 1.  1.]]
>>> print(scaler.transform([[2, 2]]))
[[3. 3.]]

See Also
--------
scale : Equivalent function without the estimator API.

:class:`~sklearn.decomposition.PCA` : Further removes the linear
    correlation across features with 'whiten=True'.

Notes
-----
```

```
|  NaNs are treated as missing values: disregarded in fit, and maintained in
|  transform.
|
|  We use a biased estimator for the standard deviation, equivalent to
|  `numpy.std(x, ddof=0)`. Note that the choice of `ddof` is unlikely to
|  affect model performance.
|
|  For a comparison of the different scalers, transformers, and normalizers,
|  see :ref:`examples/preprocessing/plot_all_scaling.py
|  <sphx_glr_auto_examples_preprocessing_plot_all_scaling.py>`.
|
|  Method resolution order:
|      StandardScaler
|      sklearn.base.TransformerMixin
|      sklearn.base.BaseEstimator
|      builtins.object
|
|  Methods defined here:
|
|  __init__(self, *, copy=True, with_mean=True, with_std=True)
|      Initialize self.  See help(type(self)) for accurate signature.
|
|  fit(self, X, y=None, sample_weight=None)
|      Compute the mean and std to be used for later scaling.
|
|      Parameters
|      ----------
|      X : {array-like, sparse matrix} of shape (n_samples, n_features)
|          The data used to compute the mean and standard deviation
|          used for later scaling along the features axis.
|
|      y : None
|          Ignored.
|
|      sample_weight : array-like of shape (n_samples,), default=None
|          Individual weights for each sample.
|
|          .. versionadded:: 0.24
|             parameter *sample_weight* support to StandardScaler.
|
|      Returns
|      -------
|      self : object
|          Fitted scaler.
|
|  inverse_transform(self, X, copy=None)
|      Scale back the data to the original representation
|
|      Parameters
|      ----------
|      X : {array-like, sparse matrix} of shape (n_samples, n_features)
|          The data used to scale along the features axis.
|      copy : bool, default=None
|          Copy the input X or not.
|
|      Returns
|      -------
|      X_tr : {ndarray, sparse matrix} of shape (n_samples, n_features)
|          Transformed array.
|
|  partial_fit(self, X, y=None, sample_weight=None)
```

```
|      Online computation of mean and std on X for later scaling.
|
|      All of X is processed as a single batch. This is intended for cases
|      when :meth:`fit` is not feasible due to very large number of
|      `n_samples` or because X is read from a continuous stream.
|
|      The algorithm for incremental mean and std is given in Equation 1.5a,b
|      in Chan, Tony F., Gene H. Golub, and Randall J. LeVeque. "Algorithms
|      for computing the sample variance: Analysis and recommendations."
|      The American Statistician 37.3 (1983): 242-247:
|
|      Parameters
|      ----------
|      X : {array-like, sparse matrix} of shape (n_samples, n_features)
|          The data used to compute the mean and standard deviation
|          used for later scaling along the features axis.
|
|      y : None
|          Ignored.
|
|      sample_weight : array-like of shape (n_samples,), default=None
|          Individual weights for each sample.
|
|          .. versionadded:: 0.24
|             parameter *sample_weight* support to StandardScaler.
|
|      Returns
|      -------
|      self : object
|          Fitted scaler.
|
|  transform(self, X, copy=None)
|      Perform standardization by centering and scaling
|
|      Parameters
|      ----------
|      X : {array-like, sparse matrix of shape (n_samples, n_features)
|          The data used to scale along the features axis.
|      copy : bool, default=None
|          Copy the input X or not.
|
|      Returns
|      -------
|      X_tr : {ndarray, sparse matrix} of shape (n_samples, n_features)
|          Transformed array.
|
|  ----------------------------------------------------------------------
|  Methods inherited from sklearn.base.TransformerMixin:
|
|  fit_transform(self, X, y=None, **fit_params)
|      Fit to data, then transform it.
|
|      Fits transformer to `X` and `y` with optional parameters `fit_params`
|      and returns a transformed version of `X`.
|
|      Parameters
|      ----------
|      X : array-like of shape (n_samples, n_features)
|          Input samples.
|
|      y :  array-like of shape (n_samples,) or (n_samples, n_outputs),
```

```
default=None
 |          Target values (None for unsupervised transformations).
 |
 |      **fit_params : dict
 |          Additional fit parameters.
 |
 |      Returns
 |      -------
 |      X_new : ndarray array of shape (n_samples, n_features_new)
 |          Transformed array.
 |
 |  ----------------------------------------------------------------------
 |  Data descriptors inherited from sklearn.base.TransformerMixin:
 |
 |  __dict__
 |      dictionary for instance variables (if defined)
 |
 |  __weakref__
 |      list of weak references to the object (if defined)
 |
 |  ----------------------------------------------------------------------
 |  Methods inherited from sklearn.base.BaseEstimator:
 |
 |  __getstate__(self)
 |
 |  __repr__(self, N_CHAR_MAX=700)
 |      Return repr(self).
 |
 |  __setstate__(self, state)
 |
 |  get_params(self, deep=True)
 |      Get parameters for this estimator.
 |
 |      Parameters
 |      ----------
 |      deep : bool, default=True
 |          If True, will return the parameters for this estimator and
 |          contained subobjects that are estimators.
 |
 |      Returns
 |      -------
 |      params : dict
 |          Parameter names mapped to their values.
 |
 |  set_params(self, **params)
 |      Set the parameters of this estimator.
 |
 |      The method works on simple estimators as well as on nested objects
 |      (such as :class:`~sklearn.pipeline.Pipeline`). The latter have
 |      parameters of the form ``<component>__<parameter>`` so that it's
 |      possible to update each component of a nested object.
 |
 |      Parameters
 |      ----------
 |      **params : dict
 |          Estimator parameters.
 |
 |      Returns
 |      -------
 |      self : estimator instance
```

```
|          Estimator instance.
```

In [8]:

```
scaler = StandardScaler().fit(X_train)
# the scaler object contains the feature means and variations in the training se
print(scaler.mean_)
print(scaler.var_)

# the scaler is used to transform the sets
X_train_prep = scaler.transform(X_train)
X_val_prep = scaler.transform(X_val)
X_test_prep = scaler.transform(X_test)
```

```
[ 2.61729782 -0.55283401]
[0.74350517 0.32379089]
```

4. Choose an evaluation metric

In [9]:

```
help(accuracy_score)
```

```
Help on function accuracy_score in module sklearn.metrics._classification:

accuracy_score(y_true, y_pred, *, normalize=True, sample_weight=None)
    Accuracy classification score.

    In multilabel classification, this function computes subset accuracy:
    the set of labels predicted for a sample must *exactly* match the
    corresponding set of labels in y_true.

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

    Parameters
    ----------
    y_true : 1d array-like, or label indicator array / sparse matrix
        Ground truth (correct) labels.

    y_pred : 1d array-like, or label indicator array / sparse matrix
        Predicted labels, as returned by a classifier.

    normalize : bool, default=True
        If ``False``, return the number of correctly classified samples.
        Otherwise, return the fraction of correctly classified samples.

    sample_weight : array-like of shape (n_samples,), default=None
        Sample weights.

    Returns
    -------
    score : float
        If ``normalize == True``, return the fraction of correctly
        classified samples (float), else returns the number of correctly
        classified samples (int).

        The best performance is 1 with ``normalize == True`` and the number
        of samples with ``normalize == False``.

    See Also
    --------
    jaccard_score, hamming_loss, zero_one_loss
```

```
    Notes
    -----
    In binary and multiclass classification, this function is equal
    to the ``jaccard_score`` function.

    Examples
    --------
    >>> from sklearn.metrics import accuracy_score
    >>> y_pred = [0, 2, 1, 3]
    >>> y_true = [0, 1, 2, 3]
    >>> accuracy_score(y_true, y_pred)
    0.5
    >>> accuracy_score(y_true, y_pred, normalize=False)
    2

    In the multilabel case with binary label indicators:

    >>> import numpy as np
    >>> accuracy_score(np.array([[0, 1], [1, 1]]), np.ones((2, 2)))
    0.5
```

Quiz

5. Choose one or more ML techniques

In [10]:

```
help(SVC)
```

```
Help on class SVC in module sklearn.svm._classes:

class SVC(sklearn.svm._base.BaseSVC)
 |  SVC(*, C=1.0, kernel='rbf', degree=3, gamma='scale', coef0=0.0, shrinking=Tr
ue, probability=False, tol=0.001, cache_size=200, class_weight=None, verbose=Fal
se, max_iter=-1, decision_function_shape='ovr', break_ties=False, random_state=N
one)
 |
 |  C-Support Vector Classification.
 |
 |  The implementation is based on libsvm. The fit time scales at least
 |  quadratically with the number of samples and may be impractical
 |  beyond tens of thousands of samples. For large datasets
 |  consider using :class:`~sklearn.svm.LinearSVC` or
 |  :class:`~sklearn.linear_model.SGDClassifier` instead, possibly after a
 |  :class:`~sklearn.kernel_approximation.Nystroem` transformer.
 |
 |  The multiclass support is handled according to a one-vs-one scheme.
 |
 |  For details on the precise mathematical formulation of the provided
 |  kernel functions and how `gamma`, `coef0` and `degree` affect each
 |  other, see the corresponding section in the narrative documentation:
 |  :ref:`svm_kernels`.
 |
 |  Read more in the :ref:`User Guide <svm_classification>`.
 |
 |  Parameters
 |  ----------
 |  C : float, default=1.0
 |      Regularization parameter. The strength of the regularization is
 |      inversely proportional to C. Must be strictly positive. The penalty
```

```
    is a squared l2 penalty.

kernel : {'linear', 'poly', 'rbf', 'sigmoid', 'precomputed'}, default='rbf'
    Specifies the kernel type to be used in the algorithm.
    It must be one of 'linear', 'poly', 'rbf', 'sigmoid', 'precomputed' or
    a callable.
    If none is given, 'rbf' will be used. If a callable is given it is
    used to pre-compute the kernel matrix from data matrices; that matrix
    should be an array of shape ``(n_samples, n_samples)``.

degree : int, default=3
    Degree of the polynomial kernel function ('poly').
    Ignored by all other kernels.

gamma : {'scale', 'auto'} or float, default='scale'
    Kernel coefficient for 'rbf', 'poly' and 'sigmoid'.

    - if ``gamma='scale'`` (default) is passed then it uses
      1 / (n_features * X.var()) as value of gamma,
    - if 'auto', uses 1 / n_features.

    .. versionchanged:: 0.22
       The default value of ``gamma`` changed from 'auto' to 'scale'.

coef0 : float, default=0.0
    Independent term in kernel function.
    It is only significant in 'poly' and 'sigmoid'.

shrinking : bool, default=True
    Whether to use the shrinking heuristic.
    See the :ref:`User Guide <shrinking_svm>`.

probability : bool, default=False
    Whether to enable probability estimates. This must be enabled prior
    to calling `fit`, will slow down that method as it internally uses
    5-fold cross-validation, and `predict_proba` may be inconsistent with
    `predict`. Read more in the :ref:`User Guide <scores_probabilities>`.

tol : float, default=1e-3
    Tolerance for stopping criterion.

cache_size : float, default=200
    Specify the size of the kernel cache (in MB).

class_weight : dict or 'balanced', default=None
    Set the parameter C of class i to class_weight[i]*C for
    SVC. 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))``

verbose : bool, default=False
    Enable verbose output. Note that this setting takes advantage of a
    per-process runtime setting in libsvm that, if enabled, may not work
    properly in a multithreaded context.

max_iter : int, default=-1
    Hard limit on iterations within solver, or -1 for no limit.

decision_function_shape : {'ovo', 'ovr'}, default='ovr'
```

```
    Whether to return a one-vs-rest ('ovr') decision function of shape
    (n_samples, n_classes) as all other classifiers, or the original
    one-vs-one ('ovo') decision function of libsvm which has shape
    (n_samples, n_classes * (n_classes - 1) / 2). However, one-vs-one
    ('ovo') is always used as multi-class strategy. The parameter is
    ignored for binary classification.

    .. versionchanged:: 0.19
        decision_function_shape is 'ovr' by default.

    .. versionadded:: 0.17
       *decision_function_shape='ovr'* is recommended.

    .. versionchanged:: 0.17
       Deprecated *decision_function_shape='ovo' and None*.

break_ties : bool, default=False
    If true, ``decision_function_shape='ovr'``, and number of classes > 2,
    :term:`predict` will break ties according to the confidence values of
    :term:`decision_function`; otherwise the first class among the tied
    classes is returned. Please note that breaking ties comes at a
    relatively high computational cost compared to a simple predict.

    .. versionadded:: 0.22

random_state : int, RandomState instance or None, default=None
    Controls the pseudo random number generation for shuffling the data for
    probability estimates. Ignored when `probability` is False.
    Pass an int for reproducible output across multiple function calls.
    See :term:`Glossary <random_state>`.

Attributes
----------
class_weight_ : ndarray of shape (n_classes,)
    Multipliers of parameter C for each class.
    Computed based on the ``class_weight`` parameter.

classes_ : ndarray of shape (n_classes,)
    The classes labels.

coef_ : ndarray of shape (n_classes * (n_classes - 1) / 2, n_features)
    Weights assigned to the features (coefficients in the primal
    problem). This is only available in the case of a linear kernel.

    `coef_` is a readonly property derived from `dual_coef_` and
    `support_vectors_`.

dual_coef_ : ndarray of shape (n_classes -1, n_SV)
    Dual coefficients of the support vector in the decision
    function (see :ref:`sgd_mathematical_formulation`), multiplied by
    their targets.
    For multiclass, coefficient for all 1-vs-1 classifiers.
    The layout of the coefficients in the multiclass case is somewhat
    non-trivial. See the :ref:`multi-class section of the User Guide
    <svm_multi_class>` for details.

fit_status_ : int
    0 if correctly fitted, 1 otherwise (will raise warning)

intercept_ : ndarray of shape (n_classes * (n_classes - 1) / 2,)
    Constants in decision function.
```

```
|
|  support_ : ndarray of shape (n_SV)
|      Indices of support vectors.
|
|  support_vectors_ : ndarray of shape (n_SV, n_features)
|      Support vectors.
|
|  n_support_ : ndarray of shape (n_classes,), dtype=int32
|      Number of support vectors for each class.
|
|  probA_ : ndarray of shape (n_classes * (n_classes - 1) / 2)
|  probB_ : ndarray of shape (n_classes * (n_classes - 1) / 2)
|      If `probability=True`, it corresponds to the parameters learned in
|      Platt scaling to produce probability estimates from decision values.
|      If `probability=False`, it's an empty array. Platt scaling uses the
|      logistic function
|      ``1 / (1 + exp(decision_value * probA_ + probB_))``
|      where ``probA_`` and ``probB_`` are learned from the dataset [2]_. For
|      more information on the multiclass case and training procedure see
|      section 8 of [1]_.
|
|  shape_fit_ : tuple of int of shape (n_dimensions_of_X,)
|      Array dimensions of training vector ``X``.
|
|  Examples
|  --------
|  >>> import numpy as np
|  >>> from sklearn.pipeline import make_pipeline
|  >>> from sklearn.preprocessing import StandardScaler
|  >>> X = np.array([[-1, -1], [-2, -1], [1, 1], [2, 1]])
|  >>> y = np.array([1, 1, 2, 2])
|  >>> from sklearn.svm import SVC
|  >>> clf = make_pipeline(StandardScaler(), SVC(gamma='auto'))
|  >>> clf.fit(X, y)
|  Pipeline(steps=[('standardscaler', StandardScaler()),
|                  ('svc', SVC(gamma='auto'))])
|
|  >>> print(clf.predict([[-0.8, -1]]))
|  [1]
|
|  See Also
|  --------
|  SVR : Support Vector Machine for Regression implemented using libsvm.
|
|  LinearSVC : Scalable Linear Support Vector Machine for classification
|      implemented using liblinear. Check the See Also section of
|      LinearSVC for more comparison element.
|
|  References
|  ----------
|  .. [1] `LIBSVM: A Library for Support Vector Machines
|      <http://www.csie.ntu.edu.tw/~cjlin/papers/libsvm.pdf>`_
|
|  .. [2] `Platt, John (1999). "Probabilistic outputs for support vector
|      machines and comparison to regularizedlikelihood methods."
|      <http://citeseer.ist.psu.edu/viewdoc/summary?doi=10.1.1.41.1639>`_
|
|  Method resolution order:
|      SVC
|      sklearn.svm._base.BaseSVC
|      sklearn.base.ClassifierMixin
```

```
 |      sklearn.svm._base.BaseLibSVM
 |      sklearn.base.BaseEstimator
 |      builtins.object
 |
 |  Methods defined here:
 |
 |  __init__(self, *, C=1.0, kernel='rbf', degree=3, gamma='scale', coef0=0.0, s
hrinking=True, probability=False, tol=0.001, cache_size=200, class_weight=None,
verbose=False, max_iter=-1, decision_function_shape='ovr', break_ties=False, ran
dom_state=None)
 |      Initialize self.  See help(type(self)) for accurate signature.
 |
 |  ----------------------------------------------------------------------
 |  Data and other attributes defined here:
 |
 |  __abstractmethods__ = frozenset()
 |
 |  ----------------------------------------------------------------------
 |  Methods inherited from sklearn.svm._base.BaseSVC:
 |
 |  decision_function(self, X)
 |      Evaluates the decision function for the samples in X.
 |
 |      Parameters
 |      ----------
 |      X : array-like of shape (n_samples, n_features)
 |
 |      Returns
 |      -------
 |      X : ndarray of shape (n_samples, n_classes * (n_classes-1) / 2)
 |          Returns the decision function of the sample for each class
 |          in the model.
 |          If decision_function_shape='ovr', the shape is (n_samples,
 |          n_classes).
 |
 |      Notes
 |      -----
 |      If decision_function_shape='ovo', the function values are proportional
 |      to the distance of the samples X to the separating hyperplane. If the
 |      exact distances are required, divide the function values by the norm of
 |      the weight vector (``coef_``). See also `this question
 |      <https://stats.stackexchange.com/questions/14876/
 |      interpreting-distance-from-hyperplane-in-svm>`_ for further details.
 |      If decision_function_shape='ovr', the decision function is a monotonic
 |      transformation of ovo decision function.
 |
 |  predict(self, X)
 |      Perform classification on samples in X.
 |
 |      For an one-class model, +1 or -1 is returned.
 |
 |      Parameters
 |      ----------
 |      X : {array-like, sparse matrix} of shape (n_samples, n_features) or
(n_samples_test, n_samples_train)
 |          For kernel="precomputed", the expected shape of X is
 |          (n_samples_test, n_samples_train).
 |
 |      Returns
 |      -------
 |      y_pred : ndarray of shape (n_samples,)
```

```
|          Class labels for samples in X.
|
|  ----------------------------------------------------------------------
|  Readonly properties inherited from sklearn.svm._base.BaseSVC:
|
|  predict_log_proba
|      Compute log probabilities of possible outcomes for samples in X.
|
|      The model need to have probability information computed at training
|      time: fit with attribute `probability` set to True.
|
|      Parameters
|      ----------
|      X : array-like of shape (n_samples, n_features) or                 (n_sa
mples_test, n_samples_train)
|          For kernel="precomputed", the expected shape of X is
|          (n_samples_test, n_samples_train).
|
|      Returns
|      -------
|      T : ndarray of shape (n_samples, n_classes)
|          Returns the log-probabilities of the sample for each class in
|          the model. The columns correspond to the classes in sorted
|          order, as they appear in the attribute :term:`classes_`.
|
|      Notes
|      -----
|      The probability model is created using cross validation, so
|      the results can be slightly different than those obtained by
|      predict. Also, it will produce meaningless results on very small
|      datasets.
|
|  predict_proba
|      Compute probabilities of possible outcomes for samples in X.
|
|      The model need to have probability information computed at training
|      time: fit with attribute `probability` set to True.
|
|      Parameters
|      ----------
|      X : array-like of shape (n_samples, n_features)
|          For kernel="precomputed", the expected shape of X is
|          (n_samples_test, n_samples_train).
|
|      Returns
|      -------
|      T : ndarray of shape (n_samples, n_classes)
|          Returns the probability of the sample for each class in
|          the model. The columns correspond to the classes in sorted
|          order, as they appear in the attribute :term:`classes_`.
|
|      Notes
|      -----
|      The probability model is created using cross validation, so
|      the results can be slightly different than those obtained by
|      predict. Also, it will produce meaningless results on very small
|      datasets.
|
|  probA_
|
|  probB_
```

```
|
|  ----------------------------------------------------------------------
|  Methods inherited from sklearn.base.ClassifierMixin:
|
|  score(self, X, y, sample_weight=None)
|      Return the mean accuracy on the given test data and labels.
|
|      In multi-label classification, this is the subset accuracy
|      which is a harsh metric since you require for each sample that
|      each label set be correctly predicted.
|
|      Parameters
|      ----------
|      X : array-like of shape (n_samples, n_features)
|          Test samples.
|
|      y : array-like of shape (n_samples,) or (n_samples, n_outputs)
|          True labels for `X`.
|
|      sample_weight : array-like of shape (n_samples,), default=None
|          Sample weights.
|
|      Returns
|      -------
|      score : float
|          Mean accuracy of ``self.predict(X)`` wrt. `y`.
|
|  ----------------------------------------------------------------------
|  Data descriptors inherited from sklearn.base.ClassifierMixin:
|
|  __dict__
|      dictionary for instance variables (if defined)
|
|  __weakref__
|      list of weak references to the object (if defined)
|
|  ----------------------------------------------------------------------
|  Methods inherited from sklearn.svm._base.BaseLibSVM:
|
|  fit(self, X, y, sample_weight=None)
|      Fit the SVM model according to the given training data.
|
|      Parameters
|      ----------
|      X : {array-like, sparse matrix} of shape (n_samples, n_features)
or (n_samples, n_samples)
|          Training vectors, where n_samples is the number of samples
|          and n_features is the number of features.
|          For kernel="precomputed", the expected shape of X is
|          (n_samples, n_samples).
|
|      y : array-like of shape (n_samples,)
|          Target values (class labels in classification, real numbers in
|          regression).
|
|      sample_weight : array-like of shape (n_samples,), default=None
|          Per-sample weights. Rescale C per sample. Higher weights
|          force the classifier to put more emphasis on these points.
|
|      Returns
|      -------
```

```
|      self : object
|
|      Notes
|      -----
|      If X and y are not C-ordered and contiguous arrays of np.float64 and
|      X is not a scipy.sparse.csr_matrix, X and/or y may be copied.
|
|      If X is a dense array, then the other methods will not support sparse
|      matrices as input.
|
|  ----------------------------------------------------------------------
|  Readonly properties inherited from sklearn.svm._base.BaseLibSVM:
|
|  coef_
|
|  n_support_
|
|  ----------------------------------------------------------------------
|  Methods inherited from sklearn.base.BaseEstimator:
|
|  __getstate__(self)
|
|  __repr__(self, N_CHAR_MAX=700)
|      Return repr(self).
|
|  __setstate__(self, state)
|
|  get_params(self, deep=True)
|      Get parameters for this estimator.
|
|      Parameters
|      ----------
|      deep : bool, default=True
|          If True, will return the parameters for this estimator and
|          contained subobjects that are estimators.
|
|      Returns
|      -------
|      params : dict
|          Parameter names mapped to their values.
|
|  set_params(self, **params)
|      Set the parameters of this estimator.
|
|      The method works on simple estimators as well as on nested objects
|      (such as :class:`~sklearn.pipeline.Pipeline`). The latter have
|      parameters of the form ``<component>__<parameter>`` so that it's
|      possible to update each component of a nested object.
|
|      Parameters
|      ----------
|      **params : dict
|          Estimator parameters.
|
|      Returns
|      -------
|      self : estimator instance
|          Estimator instance.
```

6. Tune the hyperparameters of your ML models (aka cross-validation)

In [11]:

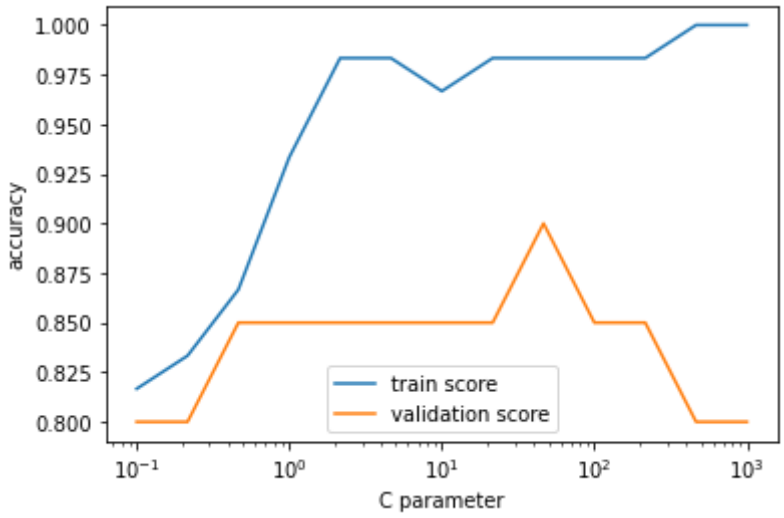
```
Cs = np.logspace(-1,3,13)
print(Cs)
train_scores = []
validation_scores = []
models = []
for C in Cs:
    classifier = SVC(kernel='rbf',C = C, probability=True) # this is our classif
    classifier.fit(X_train_prep,y_train) # the model is fitted to the training d

    y_train_pred = classifier.predict(X_train_prep)
    train_accuracy = accuracy_score(y_train,y_train_pred) # calculate the valida
    train_scores.append(train_accuracy)

    y_val_pred = classifier.predict(X_val_prep) # predict the validation set
    validation_accuracy = accuracy_score(y_val,y_val_pred) # calculate the valid
    validation_scores.append(validation_accuracy)

    models.append(classifier)
    print(C, train_accuracy, validation_accuracy)
```

```
[1.00000000e-01 2.15443469e-01 4.64158883e-01 1.00000000e+00
 2.15443469e+00 4.64158883e+00 1.00000000e+01 2.15443469e+01
 4.64158883e+01 1.00000000e+02 2.15443469e+02 4.64158883e+02
 1.00000000e+03]
0.1 0.8166666666666667 0.8
0.21544346900318834 0.8333333333333334 0.8
0.46415888336127786 0.8666666666666667 0.85
1.0 0.9333333333333333 0.85
2.1544346900318834 0.9833333333333333 0.85
4.6415888336127775 0.9833333333333333 0.85
10.0 0.9666666666666667 0.85
21.54434690031882 0.9833333333333333 0.85
46.41588833612777 0.9833333333333333 0.9
100.0 0.9833333333333333 0.85
215.44346900318823 0.9833333333333333 0.85
464.15888336127773 1.0 0.8
1000.0 1.0 0.8
```

The bias - variance tradeoff

In [12]:

```
plt.plot(Cs,train_scores,label='train score')
plt.plot(Cs,validation_scores,label='validation score')
plt.semilogx()
plt.legend()
plt.xlabel('C parameter')
plt.ylabel('accuracy')
plt.show()
```



- **high bias model** (aka underfitting)
  - it performs poorly on the train and validation sets
  - small C values in the example above
- **high variance model** (aka overfitting)
  - it performs very well on the training set but it performs poorly on the validation set
  - high C
- the goal of the parameter tuning is to find the balance between bias and variance
  - usually the best model is the one with the best validation score
  - C = 46 in our case

Quiz

How does the best model perform on the test set?

- this score tells us how well the model generalizes to previously unseen data because the test set was not touched before
- usually it is close to the best validation score

In [13]:
```
y_test_pred = models[-5].predict(X_test_prep)
print(accuracy_score(y_test, y_test_pred))
```

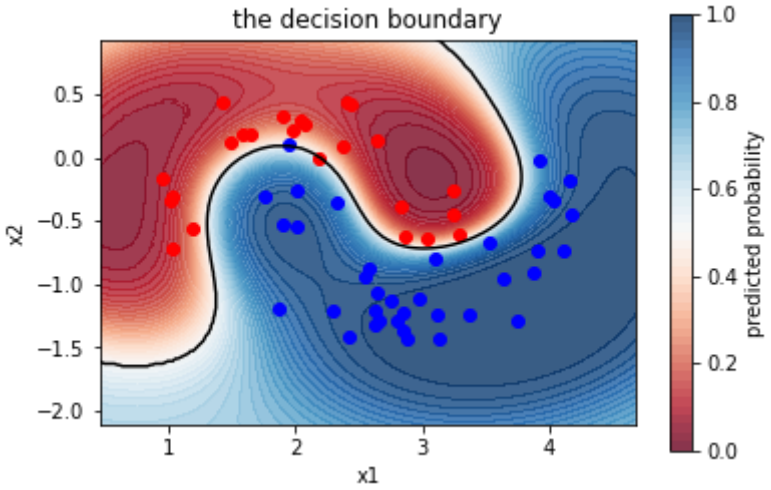
```
0.95
```

7. Interpret your model

- with two features, this is easy
- plot the decision boundary and probabilities

In [14]:
```
# Plot the decision boundary. For that, we will assign a color to each
# point in the mesh [x_min, m_max]x[y_min, y_max].

cm = plt.cm.RdBu
cm_bright = ListedColormap(['#FF0000', '#0000FF'])
h = .02  # step size in the mesh
```

```
x_min, x_max = X[:, 0].min() - .5, X[:, 0].max() + .5
y_min, y_max = X[:, 1].min() - .5, X[:, 1].max() + .5
xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                     np.arange(y_min, y_max, h))

# use the best model with C = 46
classifier = models[-5]
# scale the data before predicting! this is very important!
Z = classifier.predict_proba(scaler.transform(np.c_[xx.ravel(), yy.ravel()]))[:,

# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.contour(xx, yy, Z,vmin=0,vmax=1,levels=[0.5],colors=['k'])
plt.contourf(xx, yy, Z, cmap=cm, alpha=.8,vmin=0,vmax=1,levels=np.arange(0,1.02,
plt.colorbar(ticks=[0,0.2,0.4,0.6,0.8,1],label='predicted probability')
plt.scatter(X_train[y_train==0,0],X_train[y_train==0,1],color='r',label='class 0
plt.scatter(X_train[y_train==1,0],X_train[y_train==1,1],color='b',label='class 1
plt.xlabel('x1')
plt.ylabel('x2')
plt.title('the decision boundary')
plt.gca().set_aspect('equal')
plt.savefig('figures/decision_boundary.jpg',dpi=150)
plt.show()
```



Mud card

In [ ]: