Mud card answers

- **In terms of regression with random forests, is there a linear model that is trained on the subset of examples that reaches the end of the branch? I suppose it's a bit difficult to see how it becomes a continuous values function, is the "range" of the random tree discrete?**
- **How does a decision tree arrive at a regression prediction? The nodes are categorical, right? So is there are baseline prediction (eg. mean of target) which gets updated? How does it get updated at each node?**
  - no, it's simplier than that
  - the prediction is the target variable's mean of the examples that reach the end of the branch
  - I'm not sure what you mean by the range of the random tree
- **Can the random subset of training data selected by each single tree in random forest have overlapping samples? (Otherwise the decision trees are not independent, right?)**
  - independent with respect to trees mean that the first tree does not influence how the second tree is created
  - random forests in sklearn use all points from the training set by default unless you explicitly specify the max_samples argument
- **How are the trees in the random forest generated? Do we select a percentage of features to consider and then all combinations of those features create a tree? Do we specify what the decision points in the tree should be?**
  - yes, you decide what percentage of features to consider (the max_features argument in sklearn)
  - the rest is done automatically by sklearn
    - it randomly select a subset of features for each tree
    - it determines the most accurate tree (all decision points) given the features by minimizing a cost function
- **"I am not sure how random forest choose the features, do they can be replacement.**
  - the features are selected randomly
- **for a continuous feature, how to they choose to split it.**
  - even if you have a continuos split, the number of possible splits is finite so the best split is selected by minimizing a cost function
- **How do they choose the training data to create the decision tree.**
  - you decide what X_train and y_train are not the algorithm
- **Does the subset of training data for each tree have the same size?**
  - the same size but not the same features
  - the subset of features used by each tree can be different
- **Is there a guideline/convention for parameter tuning for tree-based models?**
  - yep, that's what we cover today
- **If we were to use sklearn's RFC, would we still have to train this with the ten people then we could use this classifier to predict likelihood of liking video games?**
  - yep, in fact I did exactly that as I was preparing the dataset :)

- **I still don't understand how the algorithm determines what the thresholds to use for each feature, and which feature to split the data by first in each tree.**
  - check out the decision tree section of `Elements of Statistical Learning` for more info
  - this book is a great resource to learn more about the ML algorithms we cover in this class
- **Is the neural network mimicking something more like a random forest?**
  - yes, it's very different
  - I'll actually have another interactive in-class exercise for DATA2040 next spring
  - we will build a neural network where students will be the neurons
- **"You said the linear regression' behavior with outlines is linear extrapolation. I am sort of wondering what's difference between interpolation and extrapolation?**
  - interpolation is between two data points
  - extrapolation is extending a prediction beyond the range of your data points
- **should the random forest use all the features or it just use some of the features. Is it select features randomly?**
  - yes, it uses a subset of features and it selects the features randomly

Supervised ML algorithms

By the end of this module, you will be able to

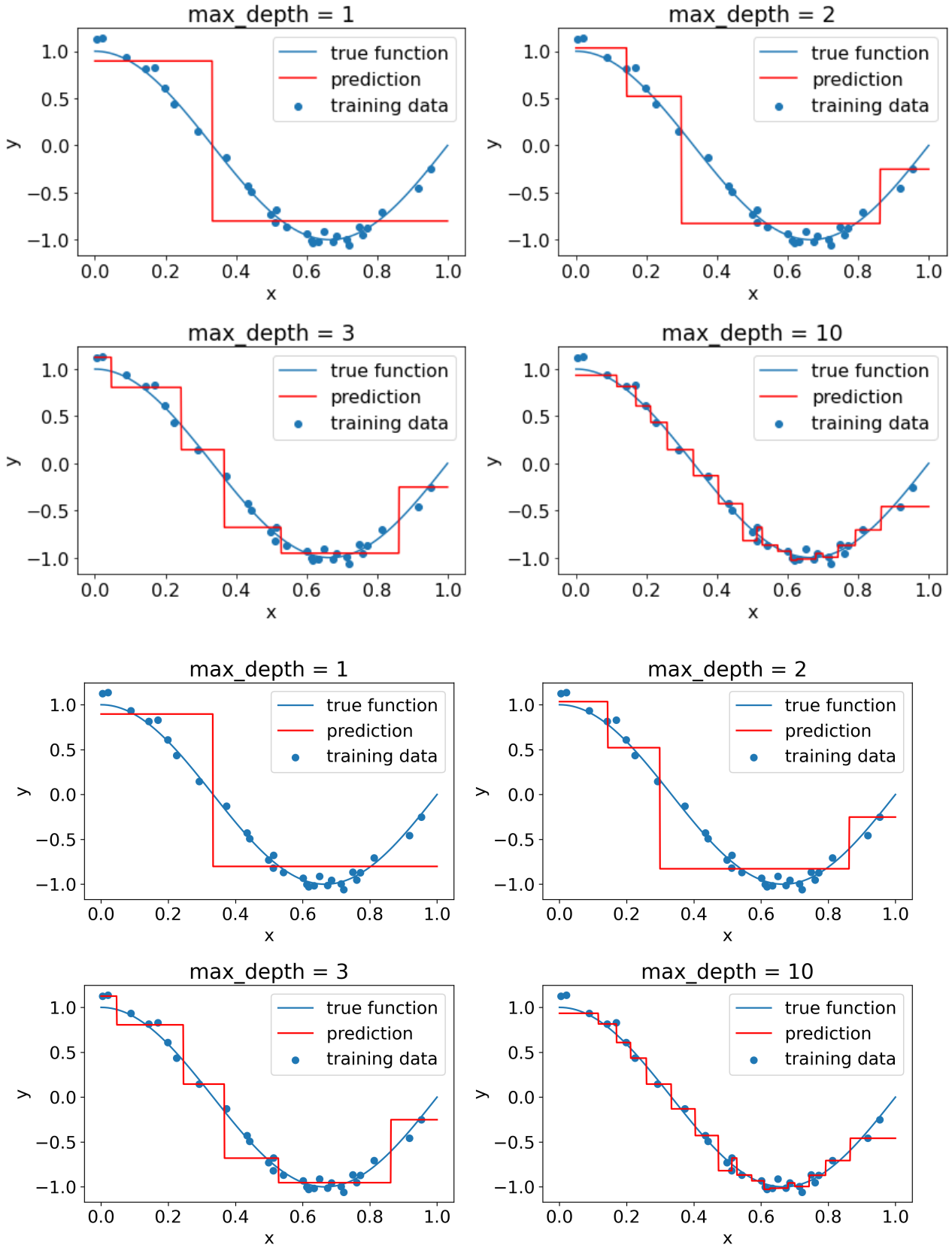
- Summarize how decision trees, random forests, and support vector machines work
- Describe how the predictions of these techniques behave in classification and regression
- Describe which hyper-parameters should be tuned

A decision tree in regression

In [1]:
```
import numpy as np
from sklearn.ensemble import RandomForestRegressor
np.random.seed(10)
def true_fun(X):
    return np.cos(1.5 * np.pi * X)

n_samples = 30

X = np.random.rand(n_samples)
y = true_fun(X) + np.random.randn(n_samples) * 0.1

X_new = np.linspace(0, 1, 1000)

reg = RandomForestRegressor(n_estimators=1,max_depth=1)
reg.fit(X[:, np.newaxis],y)
y_new = reg.predict(X_new[:, np.newaxis])
```

In [2]:
```
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams.update({'font.size': 16})
```

```
plt.figure(figsize=(12,8))

plt.subplot(2,2,1)
plt.scatter(X,y,label='training data')
plt.plot(np.linspace(0, 1, 100),true_fun(np.linspace(0, 1, 100)),label='true fun
reg = RandomForestRegressor(n_estimators=1,max_depth=1)
reg.fit(X[:, np.newaxis],y)
y_new = reg.predict(X_new[:, np.newaxis])
plt.plot(X_new,y_new,'r',label='prediction')
plt.xlabel('x')
plt.ylabel('y')
plt.title('max_depth = 1')
plt.legend()

plt.subplot(2,2,2)
plt.scatter(X,y,label='training data')
plt.plot(np.linspace(0, 1, 100),true_fun(np.linspace(0, 1, 100)),label='true fun
reg = RandomForestRegressor(n_estimators=1,max_depth=2)
reg.fit(X[:, np.newaxis],y)
y_new = reg.predict(X_new[:, np.newaxis])
plt.plot(X_new,y_new,'r',label='prediction')
plt.xlabel('x')
plt.ylabel('y')
plt.title('max_depth = 2')
plt.legend()

plt.subplot(2,2,3)
plt.scatter(X,y,label='training data')
plt.plot(np.linspace(0, 1, 100),true_fun(np.linspace(0, 1, 100)),label='true fun
reg = RandomForestRegressor(n_estimators=1,max_depth=3)
reg.fit(X[:, np.newaxis],y)
y_new = reg.predict(X_new[:, np.newaxis])
plt.plot(X_new,y_new,'r',label='prediction')
plt.xlabel('x')
plt.ylabel('y')
plt.title('max_depth = 3')
plt.legend()


plt.subplot(2,2,4)
plt.scatter(X,y,label='training data')
plt.plot(np.linspace(0, 1, 100),true_fun(np.linspace(0, 1, 100)),label='true fun
reg = RandomForestRegressor(n_estimators=1,max_depth=10)
reg.fit(X[:, np.newaxis],y)
y_new = reg.predict(X_new[:, np.newaxis])
plt.plot(X_new,y_new,'r',label='prediction')
plt.xlabel('x')
plt.ylabel('y')
plt.title('max_depth = 10')
plt.legend()

plt.tight_layout()
plt.savefig('figures/tree_reg.png',dpi=300)
plt.show()
```



How to avoid overfitting with random forests?

- tune some (or all) of following hyperparameters:
  - max_depth
  - min_samples_split

    - max_features
- With sklearn random forests, **do not tune n_estimators**!
    - the larger this value is, the better the forest will be
    - set n_estimators to maybe a 100 while tuning hyperparameters
    - increase it if necessary once the best hyperparameters are found

ML algo	suitable for large datasets?	behaviour wrt outliers	non-linear?	params to tune	smooth predictions	easy to interpret?
linear regression	yes	linear extrapolation	no	l1 and/or l2 reg	yes	yes
logistic regression	yes	scales with distance from the decision boundary	no	l1 and/or l2 reg	yes	yes
random forest regression	so so	constant	yes	max_features, max_depth	no	so so
random forest classification	tbd	tbd	tbd	tbd	tbd	tbd
SVM rbf regression	tbd	tbd	tbd	tbd	tbd	tbd
SVM rbf classification	tbd	tbd	tbd	tbd	tbd	tbd

A random forest in classification

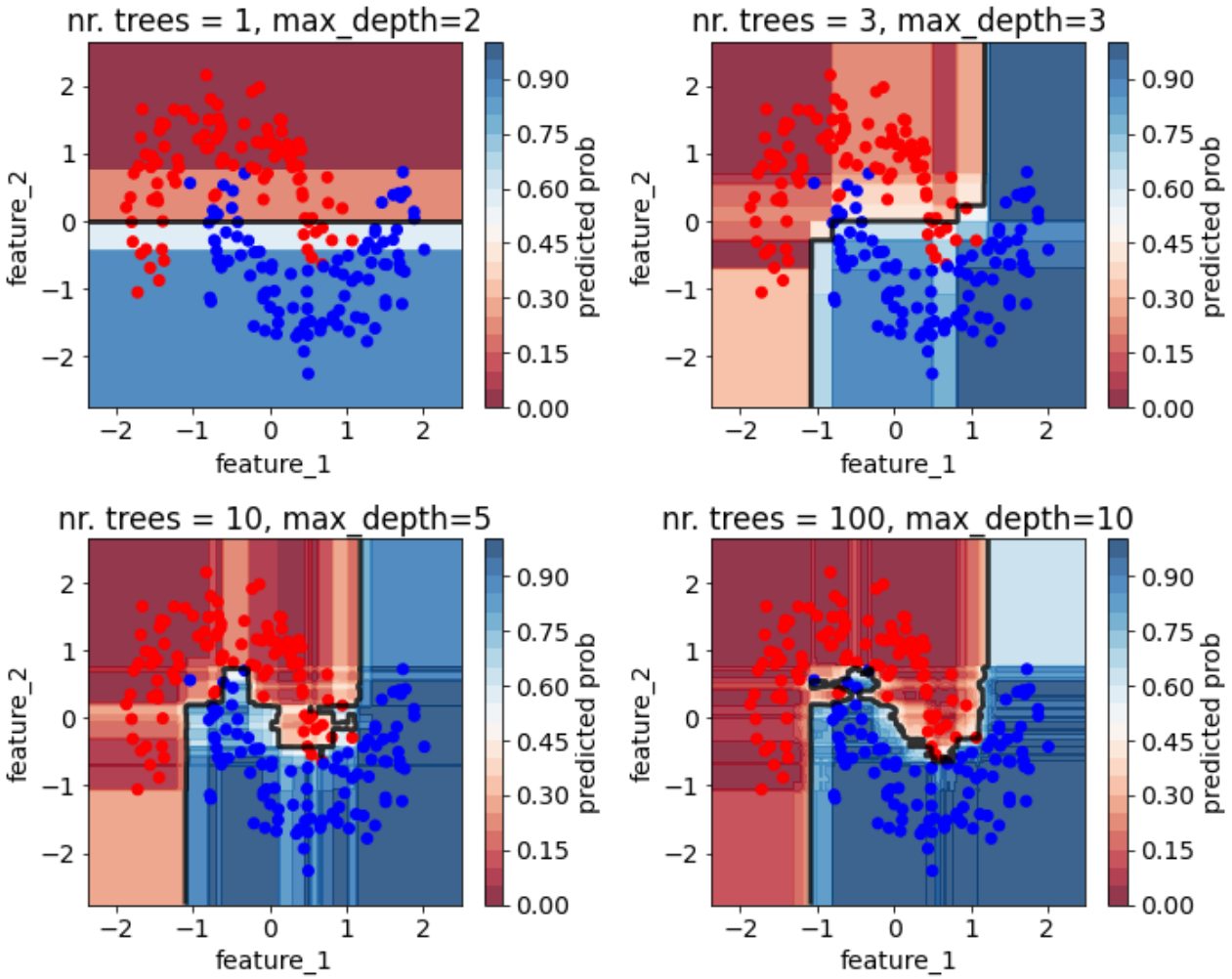
In [3]:
```
from sklearn.datasets import make_moons
import numpy as np
from sklearn.ensemble import RandomForestClassifier

# create the data
X,y = make_moons(noise=0.2, random_state=1,n_samples=200)
# set the hyperparameters
clf = RandomForestClassifier(n_estimators=1,max_depth=3,random_state=0)
# fit the model
clf.fit(X,y)
# predict new data
#y_new = clf.predict(X_new)
# predict probabilities
#y_new = clf.predict_proba(X_new)
```

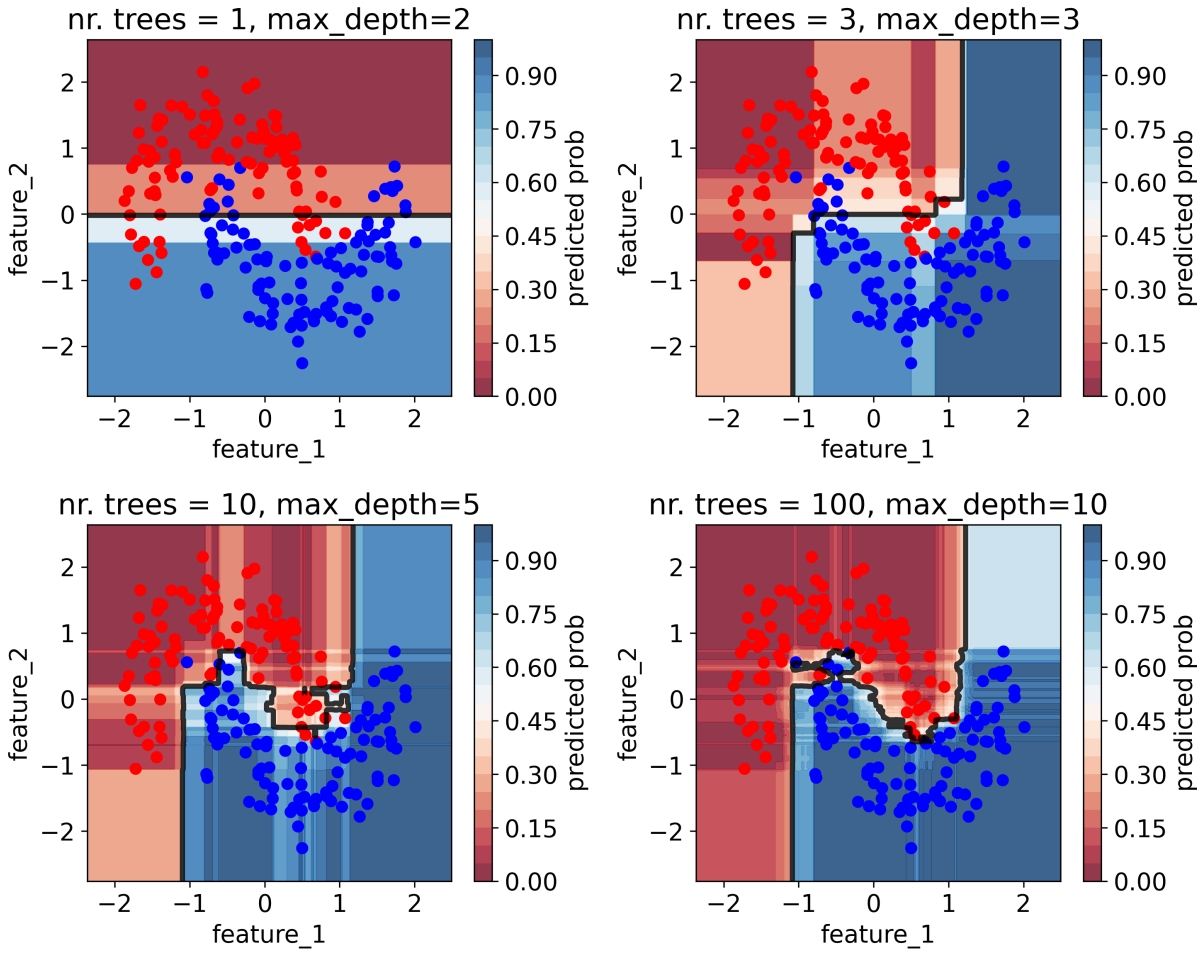
Out[3]:
```
RandomForestClassifier(max_depth=3, n_estimators=1, random_state=0)
```

In [4]:
```
from sklearn.datasets import make_moons
import numpy as np
import matplotlib.pyplot as plt
import matplotlib
from matplotlib.colors import ListedColormap
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
```

```
matplotlib.rcParams.update({'font.size': 14})

X = StandardScaler().fit_transform(X)

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))

plt.figure(figsize=(10,8))
cm_bright = ListedColormap(['#FF0000', '#0000FF'])
cm = plt.cm.RdBu

plt.subplot(2,2,1)
clf = RandomForestClassifier(n_estimators=1,max_depth=2,random_state=1)

clf.fit(X,y)
Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=cm, alpha=.8,vmin=0,vmax=1,levels=np.arange(0,1.05,
plt.colorbar(label='predicted prob')
plt.contour(xx, yy, Z, alpha=.8,vmin=0,vmax=1,levels=[0.5],colors=['k'],linewidt
plt.scatter(X[:, 0], X[:, 1], c=y,cmap=cm_bright)
plt.xlabel('feature_1')
plt.ylabel('feature_2')
plt.title('nr. trees = 1, max_depth=2')

plt.subplot(2,2,2)
clf = RandomForestClassifier(n_estimators=3,max_depth=3,random_state=4)
clf.fit(X,y)
Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=cm, alpha=.8,vmin=0,vmax=1,levels=np.arange(0,1.05,
plt.colorbar(label='predicted prob')
plt.contour(xx, yy, Z, alpha=.8,vmin=0,vmax=1,levels=[0.5],colors=['k'],linewidt
plt.scatter(X[:, 0], X[:, 1], c=y,cmap=cm_bright)
plt.xlabel('feature_1')
plt.ylabel('feature_2')
plt.title('nr. trees = 3, max_depth=3')

plt.subplot(2,2,3)
clf = RandomForestClassifier(n_estimators=10,max_depth=5,random_state=3)
clf.fit(X,y)
Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=cm, alpha=.8,vmin=0,vmax=1,levels=np.arange(0,1.05,
plt.colorbar(label='predicted prob')
plt.contour(xx, yy, Z, alpha=.8,vmin=0,vmax=1,levels=[0.5],colors=['k'],linewidt
plt.scatter(X[:, 0], X[:, 1], c=y,cmap=cm_bright)
plt.xlabel('feature_1')
plt.ylabel('feature_2')
plt.title('nr. trees = 10, max_depth=5')

plt.subplot(2,2,4)
clf = RandomForestClassifier(n_estimators=100,max_depth=10,random_state=3)
clf.fit(X,y)
```

```
Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=cm, alpha=.8,vmin=0,vmax=1,levels=np.arange(0,1.05,
plt.colorbar(label='predicted prob')
plt.contour(xx, yy, Z, alpha=.8,vmin=0,vmax=1,levels=[0.5],colors=['k'],linewidt
plt.scatter(X[:, 0], X[:, 1], c=y,cmap=cm_bright)
plt.xlabel('feature_1')
plt.ylabel('feature_2')
plt.title('nr. trees = 100, max_depth=10')


plt.tight_layout()

plt.savefig('figures/forest_clf.png',dpi=300)
plt.show()
```





ML algo	suitable for large datasets?	behaviour wrt outliers	non-linear?	params to tune	smooth predictions	easy to interpret?
linear regression	yes	linear extrapolation	no	l1 and/or l2 reg	yes	yes
logistic regression	yes	scales with distance from the decision boundary	no	l1 and/or l2 reg	yes	yes
random forest regression	so so	constant	yes	max_features, max_depth	no	so so
random forest classification	so so	step-like, difficult to tell	yes	max_features, max_depth	no	so so
SVM rbf regression	tbd	tbd	tbd	tbd	tbd	tbd
SVM rbf classification	tbd	tbd	tbd	tbd	tbd	tbd

Quiz 1

True or false?

- It is possible to create a tree with a maximum depth larger than 1 which splits on the same feature on each level/node.
- Some trees are more accurate than others so when you combine the trees into a random forest, the predictions of some trees are heavier weighted than others.
- A tree can be arbitrarily deep.
- Each node splits into two 'branches' or leaves.

Support Vector Machine

- very versatile technique, it comes in lots of flavors/types, read moree about it here
- SVM classifier motivation
  - points in n dimensional space with class 0 and 1
  - we want to find the (n-1) dimensional hyperplane that best separates the points
  - this hyperplane is our (linear) decision boundary
- we cover SVMs with radial basis functions (rbf)
  - we apply a kernel function (a non-linear transformation) to the data points
  - the kernel function basically "smears" the points
  - gaussian rbf kernel: $\exp(-\gamma(|x - x'|)^2)$ where $\gamma > 0$

SVR

In [5]:
```
import numpy as np
from sklearn.svm import SVR
np.random.seed(10)
def true_fun(X):
    return np.cos(1.5 * np.pi * X)

n_samples = 30

X = np.random.rand(n_samples)
y = true_fun(X) + np.random.randn(n_samples) * 0.1

X_new = np.linspace(-0.5, 1.5, 2000)

reg = SVR(gamma = 1, C = 1)
reg.fit(X[:, np.newaxis],y)
y_new = reg.predict(X_new[:, np.newaxis])
```

In [6]:
```
help(SVR)
```

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

class SVR(sklearn.base.RegressorMixin, sklearn.svm._base.BaseLibSVM)
 |  SVR(*, kernel='rbf', degree=3, gamma='scale', coef0=0.0, tol=0.001, C=1.0, e
psilon=0.1, shrinking=True, cache_size=200, verbose=False, max_iter=-1)
 |
 |  Epsilon-Support Vector Regression.
 |
 |  The free parameters in the model are C and epsilon.
 |
 |  The implementation is based on libsvm. The fit time complexity
```

```
|  is more than quadratic with the number of samples which makes it hard
|  to scale to datasets with more than a couple of 10000 samples. For large
|  datasets consider using :class:`~sklearn.svm.LinearSVR` or
|  :class:`~sklearn.linear_model.SGDRegressor` instead, possibly after a
|  :class:`~sklearn.kernel_approximation.Nystroem` transformer.
|
|  Read more in the :ref:`User Guide <svm_regression>`.
|
|  Parameters
|  ----------
|  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 precompute the kernel matrix.
|
|  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'.
|
|  tol : float, default=1e-3
|      Tolerance for stopping criterion.
|
|  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.
|
|  epsilon : float, default=0.1
|       Epsilon in the epsilon-SVR model. It specifies the epsilon-tube
|       within which no penalty is associated in the training loss function
|       with points predicted within a distance epsilon from the actual
|       value.
|
|  shrinking : bool, default=True
|      Whether to use the shrinking heuristic.
|      See the :ref:`User Guide <shrinking_svm>`.
|
|  cache_size : float, default=200
|      Specify the size of the kernel cache (in MB).
|
|  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.

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

    coef_ : ndarray of shape (1, 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 readonly property derived from `dual_coef_` and
        `support_vectors_`.

    dual_coef_ : ndarray of shape (1, n_SV)
        Coefficients of the support vector in the decision function.

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

    intercept_ : ndarray of shape (1,)
        Constants in decision function.

    n_support_ : ndarray of shape (n_classes,), dtype=int32
        Number of support vectors for each class.

    shape_fit_ : tuple of int of shape (n_dimensions_of_X,)
        Array dimensions of training vector ``X``.

    support_ : ndarray of shape (n_SV,)
        Indices of support vectors.

    support_vectors_ : ndarray of shape (n_SV, n_features)
        Support vectors.

    Examples
    --------
    >>> from sklearn.svm import SVR
    >>> from sklearn.pipeline import make_pipeline
    >>> from sklearn.preprocessing import StandardScaler
    >>> import numpy as np
    >>> n_samples, n_features = 10, 5
    >>> rng = np.random.RandomState(0)
    >>> y = rng.randn(n_samples)
    >>> X = rng.randn(n_samples, n_features)
    >>> regr = make_pipeline(StandardScaler(), SVR(C=1.0, epsilon=0.2))
    >>> regr.fit(X, y)
    Pipeline(steps=[('standardscaler', StandardScaler()),
                    ('svr', SVR(epsilon=0.2))])

    See Also
    --------
    NuSVR : Support Vector Machine for regression implemented using libsvm
        using a parameter to control the number of support vectors.

    LinearSVR : Scalable Linear Support Vector Machine for regression
        implemented using liblinear.

    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:
|      SVR
|      sklearn.base.RegressorMixin
|      sklearn.svm._base.BaseLibSVM
|      sklearn.base.BaseEstimator
|      builtins.object
|
|  Methods defined here:
|
|  __init__(self, *, kernel='rbf', degree=3, gamma='scale', coef0=0.0, tol=0.00
1, C=1.0, epsilon=0.1, shrinking=True, cache_size=200, verbose=False, max_iter=-
1)
|      Initialize self.  See help(type(self)) for accurate signature.
|
|  ----------------------------------------------------------------------
|  Readonly properties defined here:
|
|  probA_
|
|  probB_
|
|  ----------------------------------------------------------------------
|  Data and other attributes defined here:
|
|  __abstractmethods__ = frozenset()
|
|  ----------------------------------------------------------------------
|  Methods inherited from sklearn.base.RegressorMixin:
|
|  score(self, X, y, sample_weight=None)
|      Return the coefficient of determination :math:`R^2` of the
|      prediction.
|
|      The coefficient :math:`R^2` is defined as :math:`(1 - \frac{u}{v})`,
|      where :math:`u` is the residual sum of squares ``((y_true - y_pred)
|      ** 2).sum()`` and :math:`v` is the total sum of squares ``((y_true -
|      y_true.mean()) ** 2).sum()``. The best possible score is 1.0 and it
|      can be negative (because the model can be arbitrarily worse). A
|      constant model that always predicts the expected value of `y`,
|      disregarding the input features, would get a :math:`R^2` score of
|      0.0.
|
|      Parameters
|      ----------
|      X : array-like of shape (n_samples, n_features)
|          Test samples. For some estimators this may be a precomputed
|          kernel matrix or a list of generic objects instead with shape
|          ``(n_samples, n_samples_fitted)``, where ``n_samples_fitted``
|          is the number of samples used in the fitting for the estimator.
|
|      y : array-like of shape (n_samples,) or (n_samples, n_outputs)
|          True values for `X`.
|
```

```
|      sample_weight : array-like of shape (n_samples,), default=None
|          Sample weights.
|
|      Returns
|      -------
|      score : float
|          :math:`R^2` of ``self.predict(X)`` wrt. `y`.
|
|      Notes
|      -----
|      The :math:`R^2` score used when calling ``score`` on a regressor uses
|      ``multioutput='uniform_average'`` from version 0.23 to keep consistent
|      with default value of :func:`~sklearn.metrics.r2_score`.
|      This influences the ``score`` method of all the multioutput
|      regressors (except for
|      :class:`~sklearn.multioutput.MultiOutputRegressor`).
|
|  ----------------------------------------------------------------------
|  Data descriptors inherited from sklearn.base.RegressorMixin:
|
|  __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.
|
```

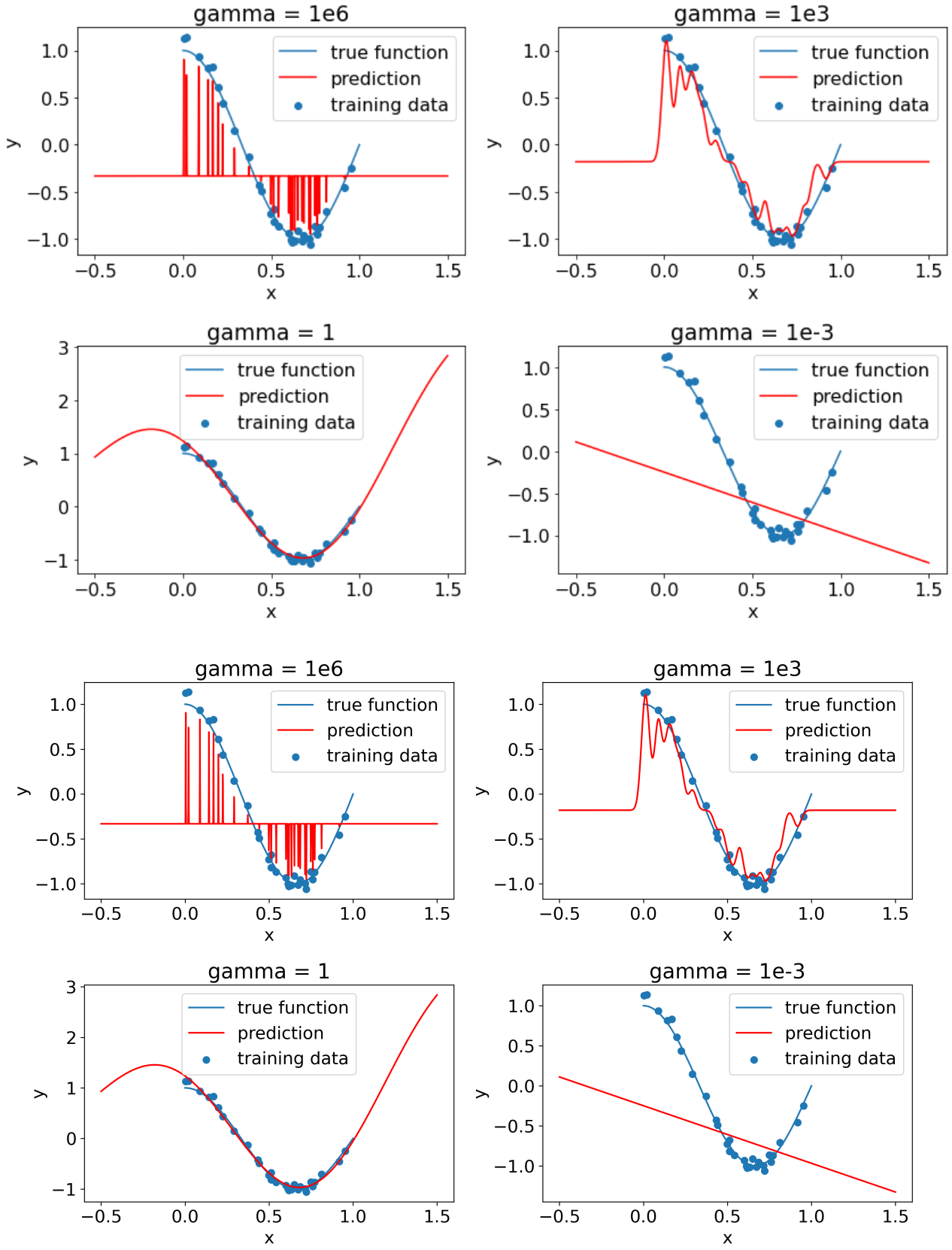
```
|  predict(self, X)
|      Perform regression on samples in X.
|
|      For an one-class model, +1 (inlier) or -1 (outlier) is returned.
|
|      Parameters
|      ----------
|      X : {array-like, sparse matrix} of shape (n_samples, n_features)
|          For kernel="precomputed", the expected shape of X is
|          (n_samples_test, n_samples_train).
|
|      Returns
|      -------
|      y_pred : ndarray of shape (n_samples,)
|
|  ----------------------------------------------------------------------
|  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.
```

In [7]:

```
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams.update({'font.size': 16})


plt.figure(figsize=(12,8))

plt.subplot(2,2,1)
plt.scatter(X,y,label='training data')
plt.plot(np.linspace(0, 1, 100),true_fun(np.linspace(0, 1, 100)),label='true fun
reg = SVR(gamma = 1000000, C = 100)
reg.fit(X[:, np.newaxis],y)
y_new = reg.predict(X_new[:, np.newaxis])
plt.plot(X_new,y_new,'r',label='prediction')
plt.xlabel('x')
plt.ylabel('y')
plt.title('gamma = 1e6')
plt.legend()

plt.subplot(2,2,2)
plt.scatter(X,y,label='training data')
plt.plot(np.linspace(0, 1, 100),true_fun(np.linspace(0, 1, 100)),label='true fun
reg = SVR(gamma = 1000, C = 100)
reg.fit(X[:, np.newaxis],y)
y_new = reg.predict(X_new[:, np.newaxis])
plt.plot(X_new,y_new,'r',label='prediction')
plt.xlabel('x')
plt.ylabel('y')
plt.title('gamma = 1e3')
plt.legend()

plt.subplot(2,2,3)
plt.scatter(X,y,label='training data')
plt.plot(np.linspace(0, 1, 100),true_fun(np.linspace(0, 1, 100)),label='true fun
reg = SVR(gamma = 1, C = 100)
reg.fit(X[:, np.newaxis],y)
y_new = reg.predict(X_new[:, np.newaxis])
plt.plot(X_new,y_new,'r',label='prediction')
plt.xlabel('x')
plt.ylabel('y')
plt.title('gamma = 1')
plt.legend()


plt.subplot(2,2,4)
plt.scatter(X,y,label='training data')
plt.plot(np.linspace(0, 1, 100),true_fun(np.linspace(0, 1, 100)),label='true fun
reg = SVR(gamma = 0.001, C = 100)
reg.fit(X[:, np.newaxis],y)
y_new = reg.predict(X_new[:, np.newaxis])
plt.plot(X_new,y_new,'r',label='prediction')
plt.xlabel('x')
plt.ylabel('y')
plt.title('gamma = 1e-3')
plt.legend()
```

```
plt.tight_layout()
plt.savefig('figures/SVM_reg.png',dpi=300)
plt.show()
```



ML algo	suitable for large datasets?	behaviour wrt outliers	non-linear?	params to tune	smooth predictions	easy to interpret?

ML algo	suitable for large datasets?	behaviour wrt outliers	non-linear?	params to tune	smooth predictions	easy to interpret?
linear regression	yes	linear extrapolation	no	l1 and/or l2 reg	yes	yes
logistic regression	yes	scales with distance from the decision boundary	no	l1 and/or l2 reg	yes	yes
random forest regression	so so	constant	yes	max_features, max_depth	no	so so
random forest classification	so so	step-like, difficult to tell	yes	max_features, max_depth	no	so so
SVM rbf regression	no	non-linear extrapolation	yes	C, gamma	yes	so so
SVM rbf classification	tbd	tbd	tbd	tbd	tbd	tbd

Quiz 2

Let's time how long it takes to fit a linear regression, random forest regression, and SVR as a function of `n_samples` using our toy regression dataset. Look up how to measure the runtime of a line or function call on stackoverflow. Set n_estimators to 10 and max_depth to 3 in the random forest. Set the gamma and C parameters to 1 in SVR. Fit models with n_samples = 1000, 2000, 3000, ..., 10000. Measure how long it takes to fit the model and plot the run time as a function of n_samples for the three models. You might need to adjust the y axis range to check some of the statements.

Which of these statements are true?

- The random forest fit time scales linearly with n_samples.
- The linear regression model is the fastest to fit.
- The SVR fit time scales worse than linear. (I.e., if we double n_sample, the fit time more than doubles.)

In [ ]:

SVC

In [8]:

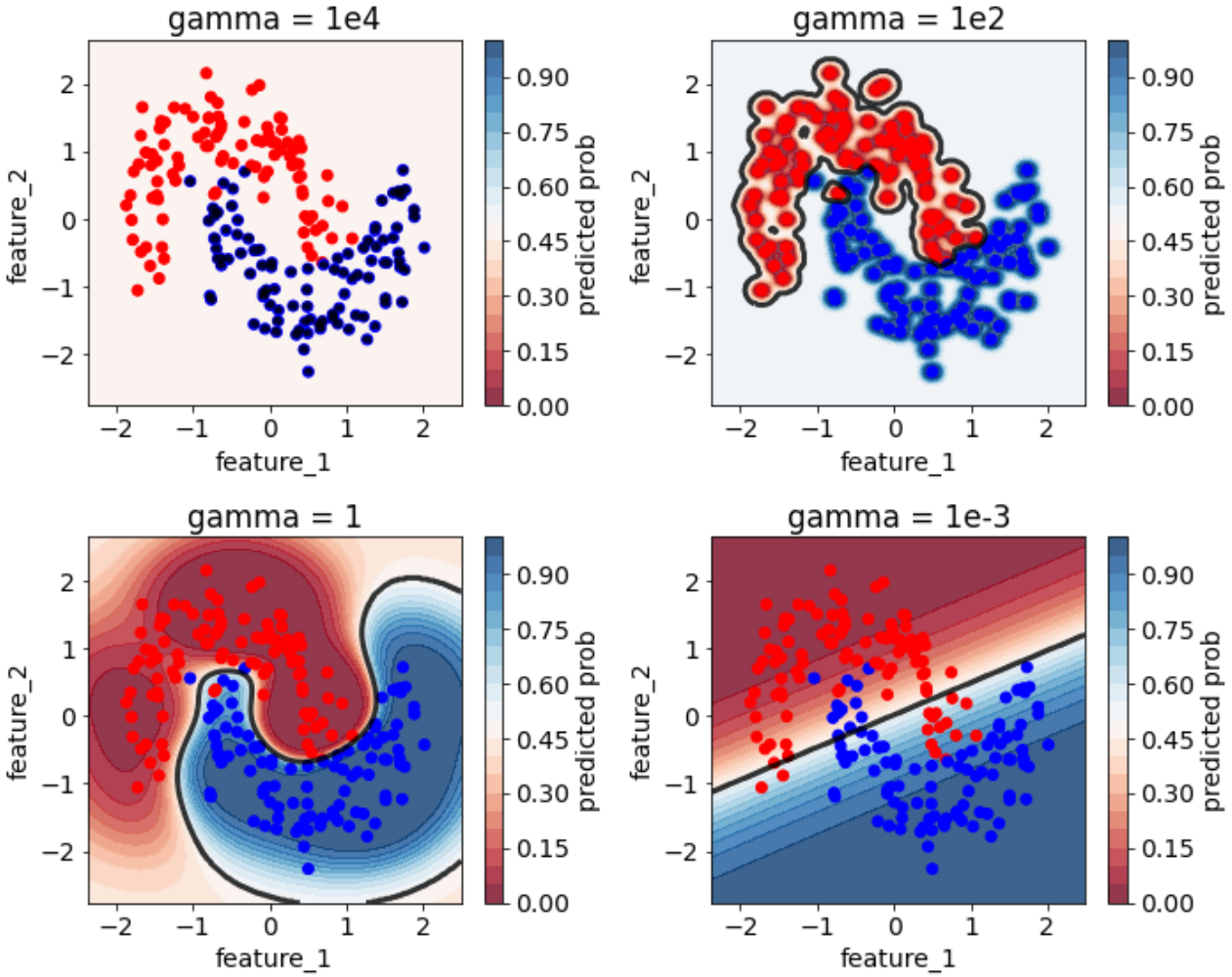
```
from sklearn.datasets import make_moons
import numpy as np
from sklearn.svm import SVC

# create the data
X,y = make_moons(noise=0.2, random_state=1,n_samples=200)
# set the hyperparameters
clf = SVC(gamma = 1, C = 1, probability=True)
# fit the model
```

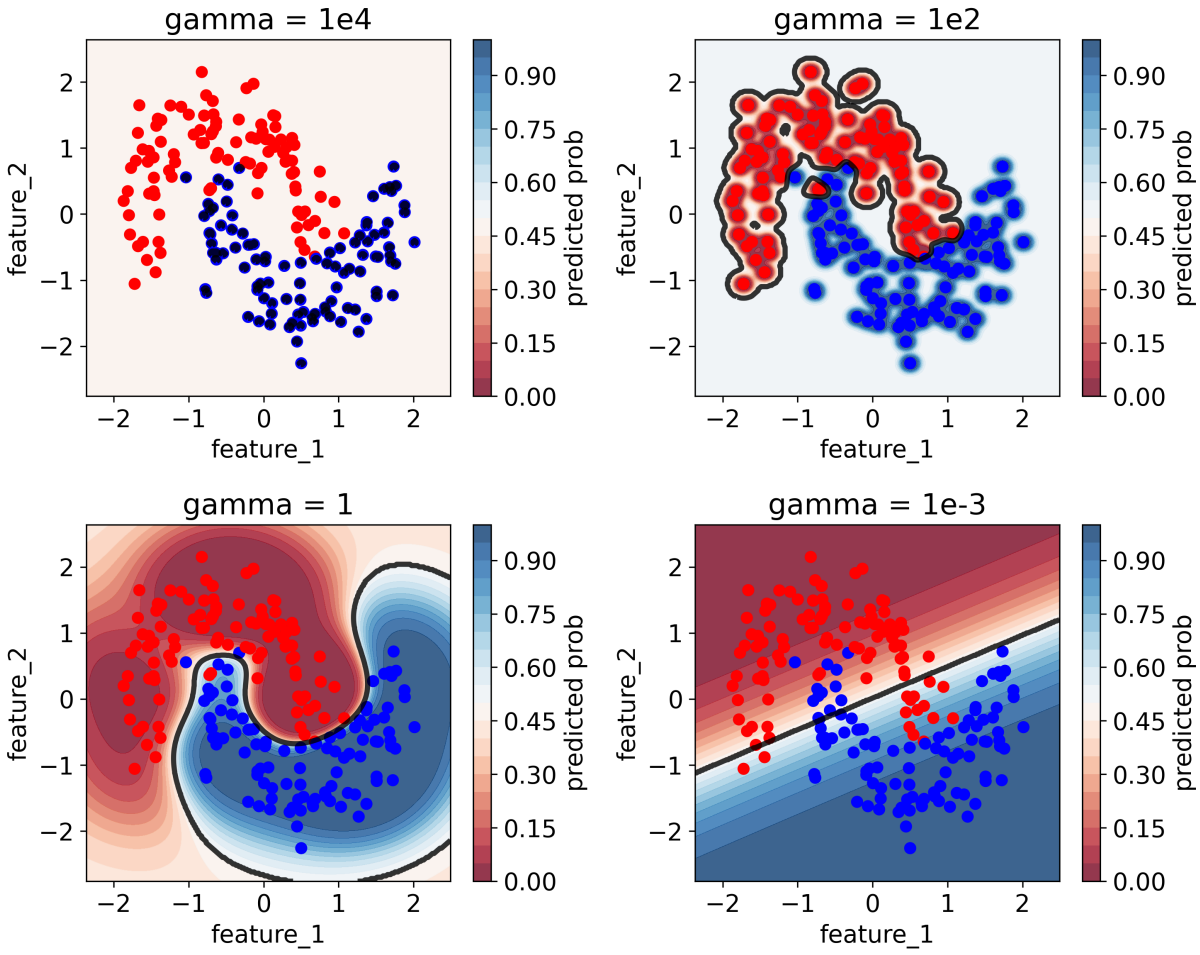
```
clf.fit(X,y)
# predict new data
#y_new = clf.predict(X_new)
# predict probabilities
#y_new = clf.predict_proba(X_new)
```

Out[8]:
```
SVC(C=1, gamma=1, probability=True)
```

In [9]:
```
from sklearn.datasets import make_moons
import numpy as np
import matplotlib.pyplot as plt
import matplotlib
from matplotlib.colors import ListedColormap
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler

matplotlib.rcParams.update({'font.size': 14})

X = StandardScaler().fit_transform(X)

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))

plt.figure(figsize=(10,8))
cm_bright = ListedColormap(['#FF0000', '#0000FF'])
cm = plt.cm.RdBu

plt.subplot(2,2,1)
clf = SVC(gamma = 1e4, C = 100, probability=True)
clf.fit(X,y)
Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=cm, alpha=.8,vmin=0,vmax=1,levels=np.arange(0,1.05,
plt.colorbar(label='predicted prob')
plt.contour(xx, yy, Z, alpha=.8,vmin=0,vmax=1,levels=[0.5],colors=['k'],linewidt
plt.scatter(X[:, 0], X[:, 1], c=y,cmap=cm_bright)
plt.xlabel('feature_1')
plt.ylabel('feature_2')
plt.title('gamma = 1e4')

plt.subplot(2,2,2)
clf = SVC(gamma = 1e2, C = 100, probability=True)
clf.fit(X,y)
Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=cm, alpha=.8,vmin=0,vmax=1,levels=np.arange(0,1.05,
plt.colorbar(label='predicted prob')
plt.contour(xx, yy, Z, alpha=.8,vmin=0,vmax=1,levels=[0.5],colors=['k'],linewidt
plt.scatter(X[:, 0], X[:, 1], c=y,cmap=cm_bright)
plt.xlabel('feature_1')
plt.ylabel('feature_2')
plt.title('gamma = 1e2')
```

```
plt.subplot(2,2,3)
clf = SVC(gamma = 1e0, C = 100, probability=True)
clf.fit(X,y)
Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=cm, alpha=.8,vmin=0,vmax=1,levels=np.arange(0,1.05,
plt.colorbar(label='predicted prob')
plt.contour(xx, yy, Z, alpha=.8,vmin=0,vmax=1,levels=[0.5],colors=['k'],linewidt
plt.scatter(X[:, 0], X[:, 1], c=y,cmap=cm_bright)
plt.xlabel('feature_1')
plt.ylabel('feature_2')
plt.title('gamma = 1')

plt.subplot(2,2,4)
clf = SVC(gamma = 1e-3, C = 100, probability=True)
clf.fit(X,y)
Z = clf.predict_proba(np.c_[xx.ravel(), yy.ravel()])[:, 1]
# Put the result into a color plot
Z = Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=cm, alpha=.8,vmin=0,vmax=1,levels=np.arange(0,1.05,
plt.colorbar(label='predicted prob')
plt.contour(xx, yy, Z, alpha=.8,vmin=0,vmax=1,levels=[0.5],colors=['k'],linewidt
plt.scatter(X[:, 0], X[:, 1], c=y,cmap=cm_bright)
plt.xlabel('feature_1')
plt.ylabel('feature_2')
plt.title('gamma = 1e-3')


plt.tight_layout()

plt.savefig('figures/SVM_clf.png',dpi=300)
plt.show()
```


gamma = 1e4
gamma = 1e2
gamma = 1
gamma = 1e-3
feature_1
feature_2
predicted prob
0.00
0.15
0.30
0.45
0.60
0.75
0.90
−2
−1
0
1
2



ML algo	suitable for large datasets?	behaviour wrt outliers	non-linear?	params to tune	smooth predictions	easy to interpret?
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logistic regression	yes	scales with distance from the decision boundary	no	l1 and/or l2 reg	yes	yes
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random forest classification	so so	step-like, difficult to tell	yes	max_features, max_depth	no	so so
SVM rbf regression	no	non-linear extrapolation	yes	C, gamma	yes	so so
SVM rbf classification	no	50-50	yes	C, gamma	yes	so so

Quiz 3

Bias variance trade off

Which gamma value gives the best trade off between high bias and high variance? Work through the steps to answer the question.

- Use random_state = 42 where-ever necessary.
- Split X, y into X_train, X_val, y_train, y_val such that 70% of the points are in train.
- Fit SVC models with C = 1, and gamma = 1e-3, 1e-2, 1e-1, 1e0, 1e1, 1e2, 1e3 on the training set.
- Measure the validation accuracy for each gamma.
- Which gamma value gives the highest validation accuracy?

In [ ]:

Mud card

In [ ]: