Graficas fourier nystroem

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In [1]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
from time import time

# Import datasets, classifiers and performance metrics
from sklearn import datasets, svm, pipeline
from sklearn.kernel_approximation import (RBFSampler,
                                          Nystroem)
from sklearn.decomposition import PCA

from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neural_network import MLPClassifier
```

In [2]:
```
# The digits dataset
digits = datasets.load_digits(n_class=9)
```

In [3]:
```
# To apply an classifier on this data, we need to flatten the image, to
# turn the data in a (samples, feature) matrix:
n_samples = len(digits.data)
data = digits.data / 16.
data -= data.mean(axis=0)
```

In [4]:
```
# We learn the digits on the first half of the digits
data_train, targets_train = (data[:n_samples // 2],
                             digits.target[:n_samples // 2])


# Now predict the value of the digit on the second half:
data_test, targets_test = (data[n_samples // 2:],
                           digits.target[n_samples // 2:])
# data_test = scaler.transform(data_test)
```

In [5]:
```
# Create a classifier: a support vector classifier
kernel_svm = svm.SVC(gamma=.2)
linear_svm = svm.LinearSVC()
```

Código propio: añado un DecisionTree sin ninguna aproximación de kernel

```
In [6]: simply_dt = DecisionTreeClassifier()
```

```
In [7]: non_overfitting_dt = DecisionTreeClassifier(min_samples_leaf=5,
                                                     max_depth = 50,
                                                     min_samples_split = 10,
                                                     min_impurity_decrease = 0.01)
```

```
In [8]: logit = LogisticRegression( C = 1e30, multi_class = 'multinomial', solver = 'lbfgs')
        # El solver por defecto no hace multinomial, solo "one-versus-rest"
        # C muy grande para minimizar la regularización
```

```
In [9]: mlp = MLPClassifier(solver='lbfgs', alpha=1e-5,
                            hidden_layer_sizes=(5, 2))
        # Dos capas ocultas, la primera con 5 neuronas, la segunda con 2
```

```
In [10]: # create pipeline from kernel approximation
         # and linear svm
         feature_map_fourier = RBFSampler(gamma=.2, random_state=1)
         feature_map_nystroem = Nystroem(gamma=.2, random_state=1)
```

```
In [11]: fourier_approx_svm = pipeline.Pipeline([("feature_map", feature_map_fourier),
                                                 ("svm", svm.LinearSVC())])

         nystroem_approx_svm = pipeline.Pipeline([("feature_map", feature_map_nystroem),
                                                  ("svm", svm.LinearSVC())])
```

Código propio: hago el pipeline con un DecisionTree Nota: de momento uso el mismo RBF-Sampler que usan ellos, la misma instancia. Si afecta puedo usar uno nuevo. No lo creo

```
In [12]: fourier_approx_dt = pipeline.Pipeline([("feature_map", feature_map_fourier),
                                                ("dt", DecisionTreeClassifier())])
```

```
In [13]: fourier_approx_logit = pipeline.Pipeline([("feature_map", feature_map_fourier),
                                                ("logit", LogisticRegression( C = 1e30,
                                                                             multi_class = 'mu
                                                                             solver = 'lbfgs')
```

```
In [14]: # fit and predict using linear and kernel svm:

         kernel_svm_time = time()
         kernel_svm.fit(data_train, targets_train)
         kernel_svm_score = kernel_svm.score(data_test, targets_test)
         kernel_svm_time = time() - kernel_svm_time

         linear_svm_time = time()
         linear_svm.fit(data_train, targets_train)
         linear_svm_score = linear_svm.score(data_test, targets_test)
         linear_svm_time = time() - linear_svm_time
```

Código propio: hago lo mismo con el DT él solo

```
In [15]: simply_dt_time = time()
         simply_dt.fit(data_train, targets_train)
         simply_dt_score = simply_dt.score(data_test, targets_test)
         simply_dt_time = time() - simply_dt_time
```

Lo de abajo es solo por probar, hay que borrarlo

```
In [16]: gg = simply_dt.decision_path(data_train)
```

```
In [17]: len(gg[0,:].toarray()[0])
```

```
Out[17]: 163
```

Código propio: hago lo mismo con logit

```
In [18]: logit_time = time()
         logit.fit(data_train, targets_train)
         logit_score = logit.score(data_test, targets_test)
         logit_time = time() - logit_time
```

Código propio: hago lo mismo con mlp

```
In [19]: mlp_time = time()
         mlp.fit(data_train, targets_train)
         mlp_score = mlp.score(data_test, targets_test)
         mlp_time = time() - mlp_time
```

Código propio: hago lo mismo con non_overfitting_dt

```
In [20]: non_overfitting_dt_time = time()
         non_overfitting_dt.fit(data_train, targets_train)
         non_overfitting_dt_score = non_overfitting_dt.score(data_test, targets_test)
         non_overfitting_dt_time = time() - non_overfitting_dt_time
```

```
In [21]: sample_sizes = 30 * np.arange(1, 10)
         fourier_scores = []
         nystroem_scores = []
         fourier_times = []
         nystroem_times = []
```

Código propio: hago las listas para mi nuevo modelo. Nota: ellos usan un nombre ambiguo. Les llaman fourier_scores y fourier_times porque solamente la svm usa fourier. Nosotros usamos fourier con dt.

```
In [22]: fourier_dt_scores = []
         fourier_dt_times = []
```

```
In [23]: fourier_logit_scores = []
         fourier_logit_times = []
```

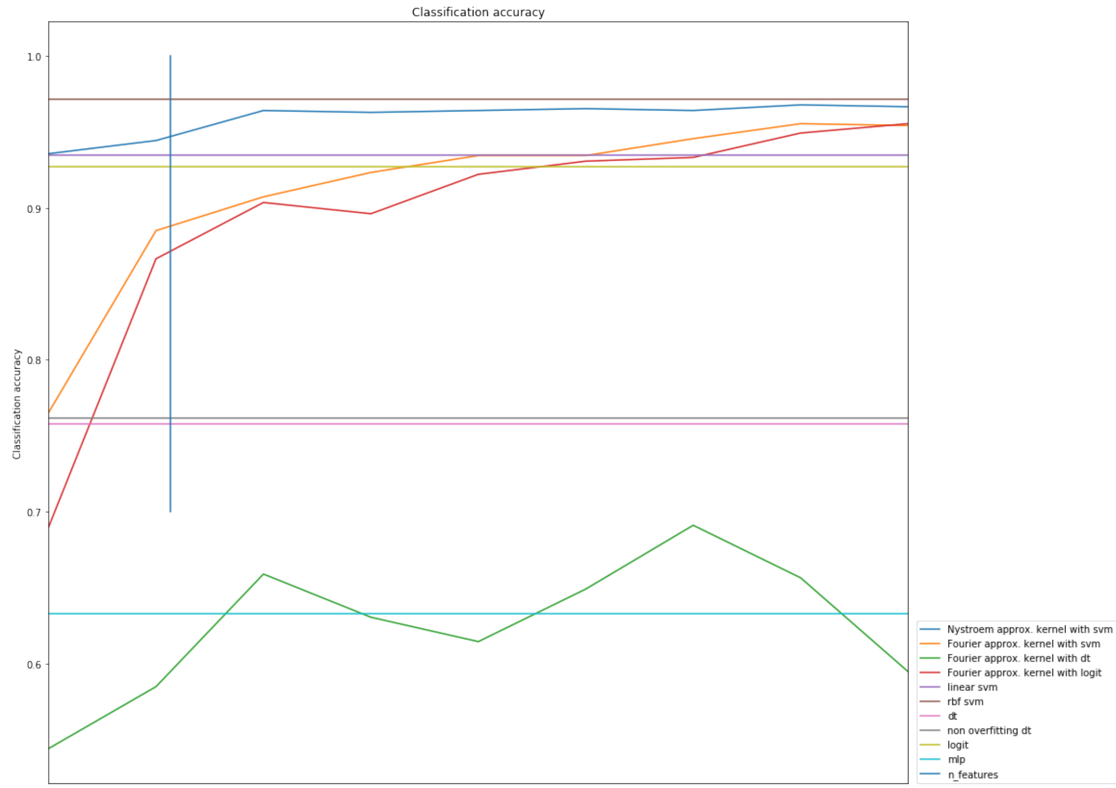
```
In [24]: for D in sample_sizes:
             fourier_approx_svm.set_params(feature_map__n_components=D)
             nystroem_approx_svm.set_params(feature_map__n_components=D)

             ##Código propio: lo mismo con mi pipeline
             fourier_approx_dt.set_params(feature_map__n_components=D)
             fourier_approx_logit.set_params(feature_map__n_components=D)

             #Nystroem svm
             start = time()
             nystroem_approx_svm.fit(data_train, targets_train)
             nystroem_times.append(time() - start)

             # Fourier svm
             start = time()
             fourier_approx_svm.fit(data_train, targets_train)
             fourier_times.append(time() - start)

             # Código propio: el tiempo del fourier dt y del fourier logit
             start = time()
             fourier_approx_dt.fit(data_train, targets_train)
             fourier_dt_times.append(time() - start)

             start = time()
             fourier_approx_logit.fit(data_train, targets_train)
             fourier_logit_times.append(time() - start)

             # Cálculo de scores
             fourier_score = fourier_approx_svm.score(data_test, targets_test)
             nystroem_score = nystroem_approx_svm.score(data_test, targets_test)

             # Código propio: calculo sl score con mi pipeline
             fourier_dt_score = fourier_approx_dt.score(data_test, targets_test)
             fourier_logit_score = fourier_approx_logit.score(data_test, targets_test)


             # Poner los scores en las listas de score
             nystroem_scores.append(nystroem_score)
             fourier_scores.append(fourier_score)

             # Código propio: pongo mis propios scores y times
             fourier_dt_scores.append(fourier_dt_score)
             fourier_logit_scores.append(fourier_logit_score)
```

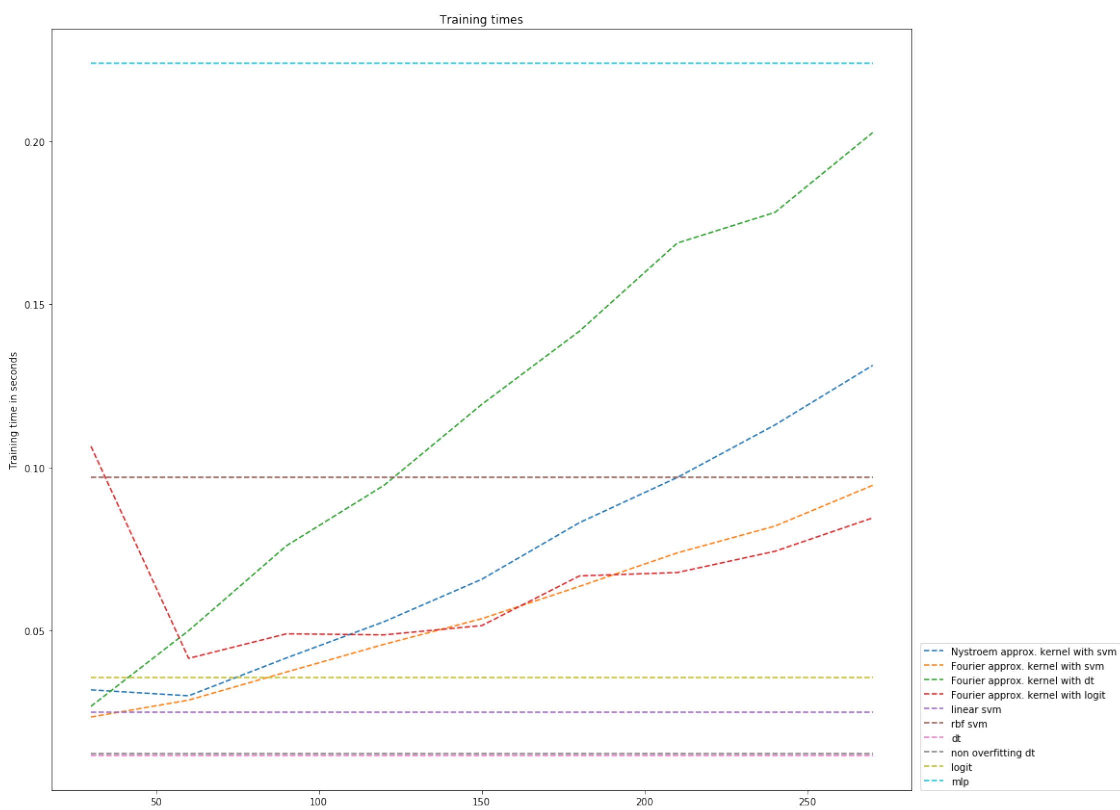
```
In [25]: # plot the results:
         plt.figure(figsize=(16, 32))
         accuracy = plt.subplot(211)
         # second y axis for timeings
```

```
timescale = plt.subplot(212)

# Accuracy y tiempo de nystroem
accuracy.plot(sample_sizes, nystroem_scores,
              label="Nystroem approx. kernel with svm")
timescale.plot(sample_sizes, nystroem_times, '--',
               label='Nystroem approx. kernel with svm')

# Accuracy y tiempo de fourier svm
accuracy.plot(sample_sizes, fourier_scores,
              label="Fourier approx. kernel with svm")
timescale.plot(sample_sizes, fourier_times, '--',
               label='Fourier approx. kernel with svm')

# Accuracy y tiempo de fourier dt
accuracy.plot(sample_sizes, fourier_dt_scores,
              label="Fourier approx. kernel with dt")
timescale.plot(sample_sizes, fourier_dt_times, '--',
               label='Fourier approx. kernel with dt')

# Accuracy y tiempo de fourier logit
accuracy.plot(sample_sizes, fourier_logit_scores,
              label="Fourier approx. kernel with logit")
timescale.plot(sample_sizes, fourier_logit_times, '--',
               label='Fourier approx. kernel with logit')

# ------------------------------------------------
# Aquí empiezan las horizontales
# ---------------------------------------

# horizontal lines for exact rbf and linear kernels:
accuracy.plot([sample_sizes[0], sample_sizes[-1]],
              [linear_svm_score, linear_svm_score], label="linear svm")
timescale.plot([sample_sizes[0], sample_sizes[-1]],
               [linear_svm_time, linear_svm_time], '--', label='linear svm')


accuracy.plot([sample_sizes[0], sample_sizes[-1]],
              [kernel_svm_score, kernel_svm_score], label="rbf svm")
timescale.plot([sample_sizes[0], sample_sizes[-1]],
               [kernel_svm_time, kernel_svm_time], '--', label='rbf svm')

# Código propio: lo mismo, las lineas horizontales para el DT simple
accuracy.plot([sample_sizes[0], sample_sizes[-1]],
              [simply_dt_score, simply_dt_score], label="dt")
timescale.plot([sample_sizes[0], sample_sizes[-1]],
               [simply_dt_time, simply_dt_time], '--', label='dt')
```

```python
    accuracy.plot([sample_sizes[0], sample_sizes[-1]],
                  [non_overfitting_dt_score, non_overfitting_dt_score], label="non overfi
    timescale.plot([sample_sizes[0], sample_sizes[-1]],
                   [non_overfitting_dt_time, non_overfitting_dt_time], '--', label='non o

    accuracy.plot([sample_sizes[0], sample_sizes[-1]],
                  [logit_score, logit_score], label="logit")
    timescale.plot([sample_sizes[0], sample_sizes[-1]],
                   [logit_time, logit_time], '--', label='logit')

    accuracy.plot([sample_sizes[0], sample_sizes[-1]],
                  [mlp_score, mlp_score], label="mlp")
    timescale.plot([sample_sizes[0], sample_sizes[-1]],
                   [mlp_time, mlp_time], '--', label='mlp')


    # vertical line for dataset dimensionality = 64
    accuracy.plot([64, 64], [0.7, 1], label="n_features")

    # legends and labels
    accuracy.set_title("Classification accuracy")
    timescale.set_title("Training times")
    accuracy.set_xlim(sample_sizes[0], sample_sizes[-1])
    accuracy.set_xticks(())
    #accuracy.set_ylim(np.min(fourier_scores), 1)
    timescale.set_xlabel("Sampling steps = transformed feature dimension")
    accuracy.set_ylabel("Classification accuracy")
    timescale.set_ylabel("Training time in seconds")
    accuracy.legend(loc=(1.01,0)) # Modifico la posición de la leyenda, que no se ve bien
    timescale.legend(loc=(1.01,0))
```

Out[25]: <matplotlib.legend.Legend at 0x7fdd63f42da0>


Classification accuracy
Classification accuracy
1.0
0.9
0.8
0.7
0.6
Nystroem approx. kernel with svm
Fourier approx. kernel with svm
Fourier approx. kernel with dt
Fourier approx. kernel with logit
linear svm
rbf svm
dt
non overfitting dt
logit
mlp
n_features


Training times
Training time in seconds
0.20
0.15
0.10
0.05
50
100
150
200
250
Sampling steps = transformed feature dimension
Nystroem approx. kernel with svm
Fourier approx. kernel with svm
Fourier approx. kernel with dt
Fourier approx. kernel with logit
linear svm
rbf svm
dt
non overfitting dt
logit
mlp

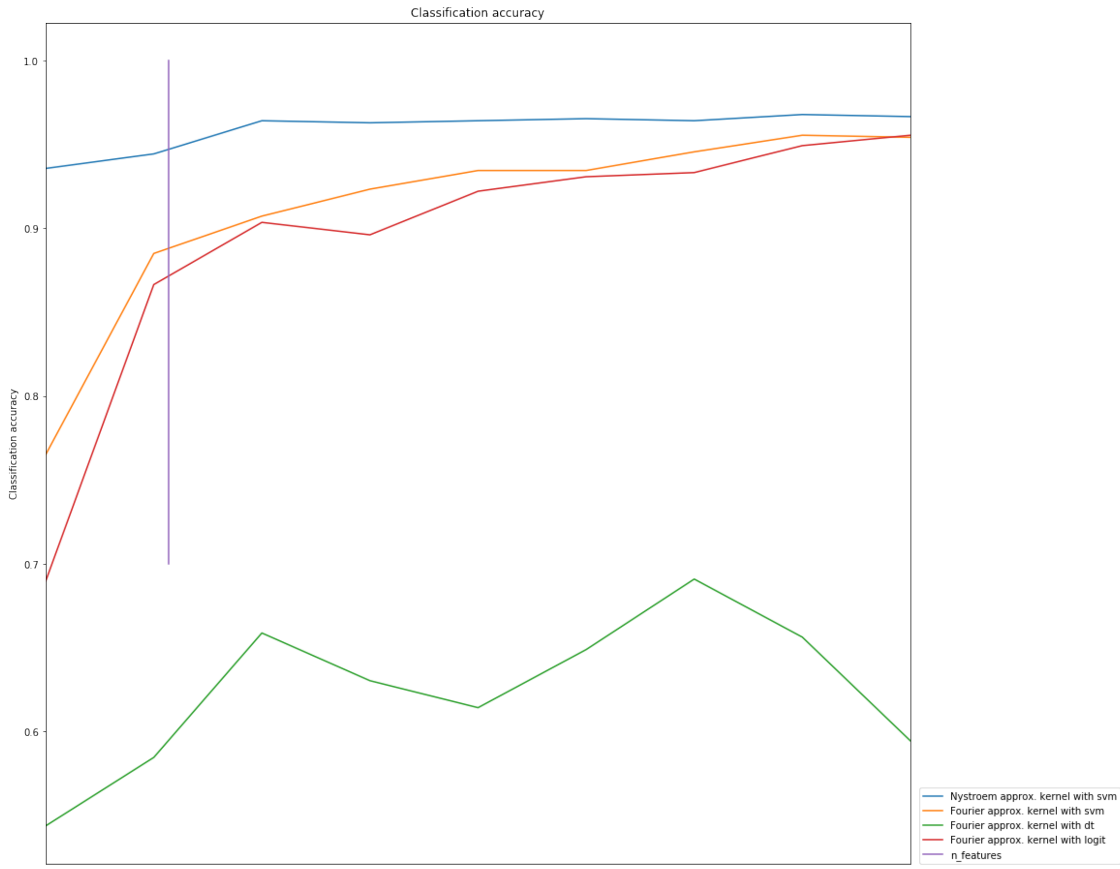
Nota: observo que el accuracy de MLP oscila mucho. A veces genial, otras fatal. Creo que es normal

0.1 Repito las gráficas para que se vean mejor

0.1.1 Solamente las aproximaciones

In [26]:
```
# plot the results:
plt.figure(figsize=(16, 16))
accuracy = plt.subplot(111)
# second y axis for timeings


# Accuracy y tiempo de nystroem
accuracy.plot(sample_sizes, nystroem_scores,
              label="Nystroem approx. kernel with svm")

# Accuracy y tiempo de fourier svm
accuracy.plot(sample_sizes, fourier_scores,
              label="Fourier approx. kernel with svm")


# Accuracy y tiempo de fourier dt
accuracy.plot(sample_sizes, fourier_dt_scores,
              label="Fourier approx. kernel with dt")


# Accuracy y tiempo de fourier logit
accuracy.plot(sample_sizes, fourier_logit_scores,
              label="Fourier approx. kernel with logit")


# vertical line for dataset dimensionality = 64
accuracy.plot([64, 64], [0.7, 1], label="n_features")

# legends and labels
accuracy.set_title("Classification accuracy")

accuracy.set_xlim(sample_sizes[0], sample_sizes[-1])
accuracy.set_xticks(())
#accuracy.set_ylim(np.min(fourier_scores), 1)

accuracy.set_ylabel("Classification accuracy")

accuracy.legend(loc=(1.01,0)) # Modifico la posición de la leyenda, que no se ve bien
```

Out[26]:
```
<matplotlib.legend.Legend at 0x7fdd63df0828>
```



0.1.2 Recortando las lineas horizontales

In [27]:
```
# plot the results:
plt.figure(figsize=(16, 16))
accuracy = plt.subplot(111)
# second y axis for timeings


# Accuracy y tiempo de nystroem
accuracy.plot(sample_sizes, nystroem_scores,
              label="Nystroem approx. kernel with svm")

# Accuracy y tiempo de fourier svm
accuracy.plot(sample_sizes, fourier_scores,
              label="Fourier approx. kernel with svm")


# Accuracy y tiempo de fourier dt
accuracy.plot(sample_sizes, fourier_dt_scores,
              label="Fourier approx. kernel with dt")
```

```python
# Accuracy y tiempo de fourier logit
accuracy.plot(sample_sizes, fourier_logit_scores,
              label="Fourier approx. kernel with logit")


# ---------------------------------------------------
# Aquí empiezan las horizontales
# ----------------------------------------

# horizontal lines for exact rbf and linear kernels:
accuracy.plot([sample_sizes[0], sample_sizes[len(sample_sizes) // 5]],
              [linear_svm_score, linear_svm_score], label="linear svm")



accuracy.plot([sample_sizes[0], sample_sizes[len(sample_sizes) // 5]],
              [kernel_svm_score, kernel_svm_score], label="rbf svm")


# Código propio: lo mismo, las lineas horizontales para el DT simple
accuracy.plot([sample_sizes[0], sample_sizes[len(sample_sizes) // 5]],
              [simply_dt_score, simply_dt_score], label="dt")


accuracy.plot([sample_sizes[0], sample_sizes[len(sample_sizes) // 5]],
              [non_overfitting_dt_score, non_overfitting_dt_score], label="non overfi


accuracy.plot([sample_sizes[0], sample_sizes[len(sample_sizes) // 5]],
              [logit_score, logit_score], label="logit")


accuracy.plot([sample_sizes[0], sample_sizes[len(sample_sizes) // 5]],
              [mlp_score, mlp_score], label="mlp")



# vertical line for dataset dimensionality = 64
accuracy.plot([64, 64], [0.7, 1], label="n_features")

# legends and labels
accuracy.set_title("Classification accuracy")

accuracy.set_xlim(sample_sizes[0], sample_sizes[-1])
accuracy.set_xticks(())
#accuracy.set_ylim(np.min(fourier_scores), 1)
```

```python
accuracy.set_ylabel("Classification accuracy")

accuracy.legend(loc=(1.01,0)) # Modifico la posición de la leyenda, que no se ve bien
```

Out[27]: <matplotlib.legend.Legend at 0x7fdd63d705c0>