En este experimento vamos a calcular la accuracy de kNN con distintos valores de k y aplicandole K-Fold Cross Validation con K=5 para ver si cambia algo al aplicar técnica. Primero corremos un script para el build de las librerias de c++ como modulos de python.

In [ ]:
```
!sh build.sh
```

Importamos librerias necesarias

In [3]:
```
from sklearn.model_selection import KFold
from sklearn.metrics import accuracy_score
from sklearn.datasets import fetch_openml
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import metnum
from utils import get_MNIST_XY
from pathlib import Path
import random
```

Obtenemos el dataset de mnist, en este caso, solo 10000 elementos por temas de tiempo de ejecucion. Dividimos el dataset en una instancia de entrenamiento con 4/5 del total de imagenes y validación con 1/5 del total. El dataset está shuffleado sobre si mismo.

In [4]:
```
X, y = get_MNIST_XY(0.8, 10000)
```

Elegimos la cantidad de k's a testear. En este caso, haremos del 1 al 130

In [5]:
```
rango_k = 130
```

Ejecutamos el loop con cada uno de los k de kNN en el rango entre 1 y rango_k y K de K-Fold con el valor 5. Luego, guardamos los resultados en accuracies

In [6]:
```
accuracies = []
for k in range(rango_k):
    print(f'Current k: {k}')
    kf = KFold(n_splits=5, shuffle=True)
    accuracies_by_split = 0
    for train_index, test_index in kf.split(X):
        X_train, X_test = X[train_index], X[test_index]
        y_train, y_test = y[train_index], y[test_index]

        clf_metnum = metnum.KNNClassifier(k)
        clf_metnum.fit(X_train, y_train)
        accuracies_by_split += accuracy_score(clf_metnum.predict(X_test), y_t
    acc_prom = accuracies_by_split/5
    accuracies.append(acc_prom)
```

```
Current k: 0
Current k: 1
Current k: 2
Current k: 3
Current k: 4
Current k: 5
Current k: 6
Current k: 7
Current k: 8
Current k: 9
```

```
Current k: 10
Current k: 11
Current k: 12
Current k: 13
Current k: 14
Current k: 15
Current k: 16
Current k: 17
Current k: 18
Current k: 19
Current k: 20
Current k: 21
Current k: 22
Current k: 23
Current k: 24
Current k: 25
Current k: 26
Current k: 27
Current k: 28
Current k: 29
Current k: 30
Current k: 31
Current k: 32
Current k: 33
Current k: 34
Current k: 35
Current k: 36
Current k: 37
Current k: 38
Current k: 39
Current k: 40
Current k: 41
Current k: 42
Current k: 43
Current k: 44
Current k: 45
Current k: 46
Current k: 47
Current k: 48
Current k: 49
Current k: 50
Current k: 51
Current k: 52
Current k: 53
Current k: 54
Current k: 55
Current k: 56
Current k: 57
Current k: 58
Current k: 59
Current k: 60
Current k: 61
Current k: 62
Current k: 63
Current k: 64
Current k: 65
Current k: 66
Current k: 67
Current k: 68
Current k: 69
Current k: 70
Current k: 71
Current k: 72
Current k: 73
Current k: 74
Current k: 75
Current k: 76
Current k: 77
Current k: 78
```

```
Current k: 79
Current k: 80
Current k: 81
Current k: 82
Current k: 83
Current k: 84
Current k: 85
Current k: 86
Current k: 87
Current k: 88
Current k: 89
Current k: 90
Current k: 91
Current k: 92
Current k: 93
Current k: 94
Current k: 95
Current k: 96
Current k: 97
Current k: 98
Current k: 99
Current k: 100
Current k: 101
Current k: 102
Current k: 103
Current k: 104
Current k: 105
Current k: 106
Current k: 107
Current k: 108
Current k: 109
Current k: 110
Current k: 111
Current k: 112
Current k: 113
Current k: 114
Current k: 115
Current k: 116
Current k: 117
Current k: 118
Current k: 119
Current k: 120
Current k: 121
Current k: 122
Current k: 123
Current k: 124
Current k: 125
Current k: 126
Current k: 127
Current k: 128
Current k: 129
```

In [7]:

```
accuracies
```

Out[7]:

```
[0.1059,
 0.9423,
 0.9425000000000001,
 0.9448000000000001,
 0.9454,
 0.9461,
 0.9424999999999999,
 0.9420999999999999,
 0.9416,
 0.9407,
 0.9387000000000001,
 0.9376999999999999,
 0.9375,
 0.9367000000000001,
```

0.9350000000000002,
0.9349000000000001,
0.9334,
0.9328,
0.9308,
0.9289,
0.9274000000000001,
0.9285,
0.9268000000000001,
0.9271,
0.925,
0.924,
0.9249,
0.9208999999999999,
0.9212,
0.9187000000000001,
0.9200999999999999,
0.9190000000000002,
0.9164,
0.9182,
0.9168,
0.9141999999999999,
0.9138,
0.9145,
0.9138999999999999,
0.9126999999999998,
0.9127000000000001,
0.9114000000000001,
0.9108,
0.9100999999999999,
0.9099999999999999,
0.908,
0.9097,
0.908,
0.9075,
0.9067000000000001,
0.9075,
0.9055,
0.9057999999999999,
0.9046000000000001,
0.9030999999999999,
0.9028,
0.9037,
0.9019999999999999,
0.9004999999999999,
0.8996999999999999,
0.8996999999999999,
0.8987999999999999,
0.8995,
0.899,
0.8987999999999999,
0.8975,
0.8965,
0.8981,
0.8977999999999999,
0.8946,
0.8940000000000001,
0.8964000000000001,
0.8951,
0.8934,
0.893,
0.8913,
0.8925000000000001,
0.8913,
0.8911,
0.8899999999999999,
0.8897,
0.8905000000000001,
0.8892,

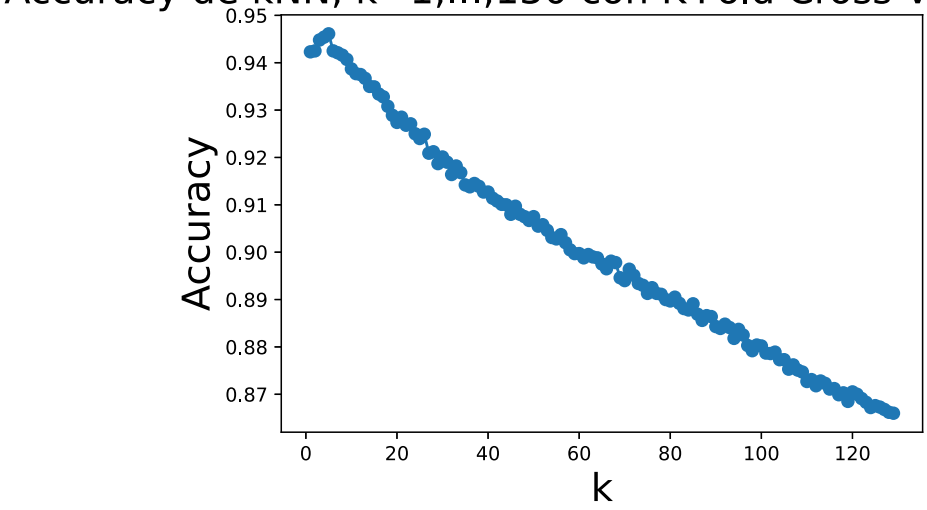
```
0.8881,
0.8878,
0.8891,
0.8869,
0.8855999999999999,
0.8865999999999999,
0.8864000000000001,
0.8843,
0.8839,
0.8847999999999999,
0.8841000000000001,
0.8817999999999999,
0.8836999999999999,
0.8825,
0.8802999999999999,
0.8792,
0.8804000000000001,
0.8802,
0.8786999999999999,
0.8785999999999999,
0.8789000000000001,
0.8773,
0.8773,
0.8753,
0.8761999999999999,
0.8751,
0.8747,
0.8727,
0.8731000000000002,
0.8718,
0.8728,
0.8723000000000001,
0.8711,
0.8712,
0.8699,
0.8703,
0.8685,
0.8705,
0.8699999999999999,
0.8690999999999999,
0.8683,
0.8672000000000001,
0.8676,
0.8673,
0.8668000000000001,
0.8662000000000001,
0.866]
```

Por último, graficamos las accuracies en función del k de kNN, todas ellas calculadas con K-Fold, K=5

In [8]:

```
plt.rc('font', size=10)
plt.rc('axes', titlesize=10)
plt.rc('axes', labelsize=10)
plt.rc('xtick', labelsize=10)
plt.rc('ytick', labelsize=10)
plt.rc('legend', fontsize=10)
plt.rc('figure', titlesize=10)

plt.plot(range(1, rango_k), accuracies[1:], '-o')
plt.xlabel('k', fontsize=20)
plt.ylabel('Accuracy', fontsize=20)
plt.title('Accuracy de kNN, k=1,...,130 con K-Fold Cross Validation, K=5', fo
plt.show()
```


Accuracy de kNN, k=1,...,130 con K-Fold Cross Validation, K=5
Accuracy
0.95
0.94
0.93
0.92
0.91
0.90
0.89
0.88
0.87
0
20
40
60
80
100
120
k