	<pre># Libraries import pandas</pre>
In [2]:	<pre>warnings.filterwarnings('ignore')  Lettura dei dataset divisi per contea.  # local file paths  dir_name = 'contea'   region_names = np.array(['A', 'B', 'C'])   region_ids = ['1286', '2061', '3101']  fp_Xtrain = []   fp_Xval = []   fp_Xtest = []   fp_ytrain = []   fp_yval = []</pre>
n [3]:	<pre>fp_ytest = []  for i in range(3):     fp_Xtrain.append(dir_name + f'/X_train{region_names[i]}.csv')     fp_Xval .append(dir_name + f'/X_val{ region_names[i]}.csv')     fp_Xtest .append(dir_name + f'/X_test{ region_names[i]}.csv')     fp_ytrain.append(dir_name + f'/y_train{region_names[i]}.csv')     fp_yval .append(dir_name + f'/y_val{ region_names[i]}.csv')     fp_ytest .append(dir_name + f'/y_test{ region_names[i]}.csv')  # Lettura dei dati  X_train = []     X_val = []     X_test = []     y_train = []</pre>
	<pre>y_val = [] y_test = []  for i in range(3):     X_train.append(pd.read_csv(fp_Xtrain[i], low_memory=False))     X_val .append(pd.read_csv(fp_Xval [i], low_memory=False))     X_test .append(pd.read_csv(fp_Xtest [i], low_memory=False))     y_train.append(pd.read_csv(fp_ytrain[i], low_memory=False))     y_val .append(pd.read_csv(fp_yval [i], low_memory=False))     y_test .append(pd.read_csv(fp_ytest [i], low_memory=False))  X_train = np.array(X_train, dtype=object) X_val = np.array(X_val, dtype=object) Y_train = np.array(X_test, dtype=object) y_train = np.array(y_train, dtype=object) y_val = np.array(y_val, dtype=object)</pre>
n [4]:	<pre>def dimensionality(y=False):     for i in range(3):         print(f'X_train{region_names[i]}: {X_train[i].shape}')         print(f'X_val{region_names[i]}: {X_val [i].shape}')         print(f'X_test{region_names[i]}: {X_test [i].shape}')         if y:             print(f'y_train{region_names[i]}: {y_train[i].shape}')             print(f'y_val{region_names[i]}: {y_val [i].shape}')             print(f'y_test{region_names[i]}: {y_val [i].shape}')             print(f'y_test{region_names[i]}: {y_test [i].shape}')             print(f'y_test{region_names[i]}: {y_test [i].shape}')             print(f'y_test{region_names[i]}: {y_test [i].shape}')</pre>
	<pre>X_trainA: (26819, 69) X_valA: (9006, 69) X_testA: (9085, 69) y_trainA: (26819, 1) y_valA: (9006, 1) y_testA: (9085, 1)  X_trainB: (8119, 69) X_valB: (2658, 69) X_testB: (2606, 69) y_trainB: (8119, 1) y_valB: (2658, 1) y_valB: (2658, 1) y_testB: (2606, 1)</pre>
	<ul> <li>X_valC: (21908, 69)</li> <li>X_testC: (21876, 69)</li> <li>Y_trainc: (64771, 1)</li> <li>Y_valC: (21908, 1)</li> <li>Y_testC: (21876, 1)</li> </ul> Definizione di un Subset per la costruzione del modello Gli algoritmi usati in questo notebook hanno un costo computazionale elevato, per questo è definito un sottoinsieme dei dataset originali su cui far girare gli algoritmi; questo per facilitare la fase di creazione e di testing e ottenere risultati verosimili in tempi utili a verificare il corretto funzionamento del processo. Nella versione finale gli algoritmi usaranno la totalità delle instanze del dataset originale.
n [6]: n [7]: n [8]:	<pre>#sub_perc = [1/1000, 1/100, 1/1000] # A: 100, B: 100, C: 100; Test rapido</pre>
[9]: [10]:	<pre>for i in range(3):     X_sub, y_sub = resample(X_train[i], y_train[i], n_samples = int(sub_perc[i]*len(X_train[i])))     X_train_sub.append(X_sub)     y_train_sub.append(y_sub)  Variabili globali  # Globals N_ESTIMATORS = 80 CV = 5 SCORING = 'neg_mean_squared_error'</pre>
	Importanza delle Feature: Random Forest  Il primo luogo è allenato un RandomForestRegressor, da cui si può ricavare il ranking delle feature per importanza (si fa supporto di un barplot per una rappresentazione grafica di questa informazione).  Sulla base del ranking ottenuto viene anche modellato il miglior modello per numero di feature usate sulla base del mean squared error: si itera sul numero di feature usate aggiunendone una alla volta in base al ranking. (Anche per questo tipo di informazione è fornito un grafico).  plt.rcParams.update({'font.size': 35})
[12]:	<pre>def createRF(X, y):     rf = RandomForestRegressor(         n_estimators = N_ESTIMATORS,         n_jobs = N_JOBS     )     rf.fit(X, y.values.ravel())     return rf  def barplot(X, rf, reg_name, file_name=''):     print(f'{reg_name} FEATURE IMPORTANCES')     print(list(X.columns[np.argsort(rf.feature_importances_)[::-1]]))     print()     fig, ax = plt.subplots(figsize=(len(rf.feature_importances_)/2,10))</pre>
	<pre>ax.tick_params(axis='x', which='major', labelsize=15) ax.tick_params(axis='x', which='minor', labelsize=20) ax.tick_params(axis='y', which='major', labelsize=25) ax.tick_params(axis='y', which='minor', labelsize=30)  ax.bar(range(0, X.shape[1]), rf.feature_importances_) ax.set_title("Feature Importances") ax.set_title("Feature Importances") ax.set_xticks(range(X.shape[1])) ax.set_xticklabels(X.columns, rotation=90)  ax.grid()  if file_name != '':     fig.savefig('images/' + file_name + '_all_feature_importances.jpg')</pre>
[14]:	<pre>def compute_rmse(X, y, bf, debug=False):     rmse = []     for f in range(1, len(bf)+1):         if debug:             print(f)          rf_small = RandomForestRegressor(</pre>
[15]:	<pre>x.loc[:,cols],     y.values.ravel(),     cv = CV,     scoring = SCORING, )     rmse += [-scores.mean()]  return rmse  def feature_plot(rmse, reg_name, file_name=''):     min_ = min(rmse)     best = np.argmin(rmse) + 1  print(f'{reg name} INCRESAING n-FEATURE PLOT')</pre>
	<pre>print ("Full score:", rmse[-1]) print ("Best score:", min_) print("Best number of feature: ", best) print()  fig, ax = plt.subplots(figsize=(len(rmse)/2, 10))  ax.tick_params(axis='x', which='major', labelsize=25) ax.tick_params(axis='x', which='minor', labelsize=30) ax.tick_params(axis='y', which='major', labelsize=30) ax.tick_params(axis='y', which='minor', labelsize=35)  ax.plot(range(1, len(rmse)+1), rmse, 'o-', label="RMSE") ax.set_title("RMSE on varying features") ax.set_xlabel("Number of Best features used")</pre>
[16]:	<pre>ax.grid()  if file_name != '':     fig.savefig('images/' + file_name + '_increasing_rmse.jpg')  def feature_importance(X, y, reg_name, debug=False, file_name=''):     rf = createRF(X, y)     barplot(X, rf, reg_name, file_name=file_name)     best_features = np.argsort(rf.feature_importances_)[::-1]     rmse = compute_rmse(X, y, best_features, debug=debug)</pre>
[17]:	<pre>def feat_importance(index, debug=False, file_name=''):     if file_name == '':         file_name = region_ids[index]     return feature_importance(</pre>
[18]:	Prima Contea 1286  %%time  feat_importance(
	secode_122', 'propertylandusetypeid_266.0', 'unitcnt_na_flag', 'heatingorsystemtypeid_13.0', 'propertylandusetypeid_248.0', 'heatingorsystemtypeid_7.0', 'heatingorsystemtypeid_18.0', 'heatingorsystemtypeid_10.0', 'propertylandusetypeid_263.0', 'heatingorsystemtypeid_11.0' 'propertylandusetypeid_269.0', 'heatingorsystemtypeid_11.0' 'propertycountylandusecode_010C', 'propertyzoningdesc_LARS', 'buildingqualitypeid', 'propertyzoningdesc_LARD1.5', 'propertyzoningdesc_LAR3', 'propertyzoningdesc_LAR1', 'propertylandusetypeid_275.0', 'propertyzoningdesc_LARN', 'propertylandusetypeid_267.0', 'heatingorsystemtypeid_2.0', 'propertylandusetypeid_265.0', 'propertylandusetypeid_264.0', 'fips_6111.0', 'fips_6059.0', 'fips_6037.0', 'heatingorsystemtypeid_12.0', 'buildingqualitytypeid_na_flag', 'propertylandusetypeid_31.0', 'heatingorsystemtypeid_20.0', ropertycountylandusecode_0100', 'propertyzoningdesc_rare']  A INCRESAING n-FEATURE PLOT Full score: 0.0035387929552893084 Best score: 0.0035037512427053934 Best number of feature: 31  Wall time: 51min 16s
	Feature Importances  0.07  0.06  0.05  0.001  0.002  0.001  0.002  0.001  0.002  0.002  0.003  0.002  0.003  0.002  0.003  0.004  0.003  0.004  0.004  0.005  0.005  0.006  0.005  0.006  0.007  0.006  0.007  0.006  0.007  0.006  0.007  0.006  0.007  0.006  0.007
	D. 100000  Septimoral descriptions of the pathnoment of the pathno
[19]:	0.0040 0.0035 0 10 20 30 40 50 60 70  Number of Best features used  Seconda Contea 2061  %%time feat_importance(
	B FEATURE IMPORTANCES ['longitude', 'structuretaxvaluedollarcnt', 'lotsizesquarefeet', 'int_transactiondate', 'living_area_prop', 'x_prop', 'latitude', 'tax_ratio', 'landtaxvaluedollarcnt', 'taxamount', 'taxvaluedollarcnt', 'yearbuilt', 'fi shedsquarefeet12', 'calculatedfinishedsquarefeet', 'neighborhood_mean_price', 'period_mean_price', 'regionidz p', 'roomcnt', 'rawcensustractandblock', 'bedroomcnt', 'regionidcity', 'bathroomcnt', 'calculatedbathnbr', 'fe eplacecnt', 'poolcnt_1.0', 'propertylandusetypeid_265.0', 'assessmentyear_2015.0', 'propertylandusetypeid_275.0', 'propertylandusetypeid_266.0', 'propertylandusetypeid_261.0', 'propertylandusetypeid_246.0', 'propertylandusetypeid_247.0', 'unitcnt', 'propertylandusetypeid_248.0', 'propertylandusetypeid_269.0', 'unitcnt_na_flag', ropertylandusetypeid_31.0', 'propertylandusetypeid_263.0', 'buildingqualitytypeid', 'buildingqualitytypeid_na_lag', 'propertyzoningdesc_rare', 'fips_6037.0', 'fips_6059.0', 'propertyzoningdesc_LARS', '
	ypeid_10.0', 'heatingorsystemtypeid_7.0', 'propertyzoningdesc_LBR1N', 'heatingorsystemtypeid_2.0', 'heatingorsystemtypeid_6.0']  B INCRESAING n-FEATURE PLOT Full score: 0.003950691598601619 Best score: 0.00390728526283164 Best number of feature: 53  Wall time: 11min 35s  Feature Importances  0.07  0.06  0.05
	buildingqualitypeld acid displacement in the decidence of finishedsquarefeet fraweeusatterandlock regionidary product and collection of the production of th
	RMSE on varying features  0.00575 0.00550 0.00525 0.00475 0.00450 0.00425 0.00400
	0.000  Number of Best features used  Analisi dei risultati  Il comportamento è simile per tutte le contee, seppur per la prima il miglior mean squared error si ottenga con una trentina di feature mentre per la seconda e terza il numero ottimale sia di circa 50, l'andamento e il valore finale dell'errore è comparabile.  Per tutte e ter l'importanza delle variabili è analoga:  • l'attitude e longitude sono molto importanti, segno che la posizione geografica ha una certa rilevanza. • la colonna int_transactiondate ha una gran rilevanza, sintomo che il periodo di ventina nell'anno è molto significativo.
	<ul> <li>la colonna int_transactiondate ha una gran rilevanza, sintomo che il periodo di ventina nell'anno e molto significativo.</li> <li>le colonne relative alle tasse sono quelle che spiccano per importanza, probabilmente perché grandezze che includono più fattori, tra cui spiccano le due colonne aggiunte in fase di preparazione tax_ratio e tax_prop.</li> <li>le altre tre colonne sintetiche period_mean_price, neighborhood_mean_price e living_area_prop sono tra le più importanti</li> <li>tutte le feature generate dal One-Hot-Encoding di fips e heatingorsystemtypeid non sono importanti.</li> <li>invece feature generate dal One-Hot-Encoding come propertylandusetypeid o propertyzoningdesc hanno se sommate nel complesso una certa importanza.</li> <li>Importanza delle feature: Selezione Ricorsiva</li> <li>Il ranking delle feature attraverso la RandomForest non è del tutto affidabile: due variabili molto correlate sono in competizione per portare lo stesso tipo di informazione, se questa informazione fosse elevata entrambe avrebbero uno score medio; sarebbe invece preferibile avere un unica feature con uno score molto alto.</li> </ul>
	Per permettere ciò utilizzo una <b>selezione ricorsiva 1-step</b> : ad ogni passo rialleno un albero e scarto la feature con importanza minore.  Questo processo permette di evitare il rischio prima descritto: eliminando una delle due feature che sono fortemente correlate e che potrebbero avere uno score medio, all'iterazione successiva avendo un'unica feature questa avrà uno score molto alto. <b>def</b> get_selector(X, y):     rf_small = RandomForestRegressor(
[22]:	<pre>n_jobs = N_JOBS ) selector.fit(X, y.values.ravel()) return selector  def selector_info(sel, X):     print("SELECTOR")     print("Numero di Feature selezionate: ", sel.n_features_)     print("Feature: \n", list(X.columns[sel.support_]))     print()     print("Ranking delle feature: \n", list(X.columns[np.argsort(sel.ranking_)][:sel.n_features_]))     print()     return list(X.columns[np.argsort(sel.ranking_)][:sel.n_features_])</pre>
[23]: [24]: [25]:	<pre>def recursive_selection(X, y):     selector = get_selector(X, y)     selected = selector_info(selector, X)     return selected  feat_selected = []  def get_selected(index):     return recursive selection(</pre>
[26]:	<pre>X_train_sub[index],     y_train_sub[index] )  Prima Contea 1286  %%time     feat_selected.append(get_selected(0))  SELECTOR Numero di Feature selezionate: 55 Feature: ['bathroomcnt', 'bedroomcnt', 'buildingqualitytypeid', 'calculatedbathnbr', 'calculatedfinishedsquarefeet',</pre>
	inishedsquarefeet12', 'fireplacecnt', 'latitude', 'longitude', 'lotsizesquarefeet', 'rawcensustractandblock',
	inishedsquarefeet12', 'fireplacent', 'latitude', 'longitude', 'lotsizesquarefeet', 'rawcensustractandblock', 'regionidcity', 'regionidcity', 'romcnot', 'unitcnt', 'yearbuilt', 'structuretaxvaluedollarcnt', 'taxvaluedollarcnt', 'taxamount', 'int_transactiondate', 'period_mean_price', 'neighborhood_mean_prie', 'living_area_prop', 'tax_ratio', 'tax_prop', 'buildingqualitytypeid_na_flag', 'unitcnt_na_flag', 'assessntyear_2015.0', 'heatingorsystemtypeid_1.0', 'heatingorsystemtypeid_10.0', 'heatingorsystemtypeid_11.0', 'heatingorsystemtypeid_12.0', 'heatingorsystemtypeid_13.0', 'heatingorsystemtypeid_18.0', 'heatingorsystemtypeid_24.0', 'poolcnt_1.0', 'propertycountylandusecode_0100', ropertycountylandusecode_122', 'propertycountylandusecode_34', 'propertycountylandusecode_rare', 'propertylasetypeid_31.0', 'propertylandusetypeid_246.0', 'propertylandusetypeid_248.0', ropertylandusetypeid_260.0', 'propertylandusetypeid_261.0', 'propertylandusetypeid_263.0', 'propertylandusetypeid_260.0', 'propertylandusetypeid_261.0', 'propertylandusetypeid_269.0']  Ranking delle feature: ['bathroomcnt', 'heatingorsystemtypeid_7.0', 'heatingorsystemtypeid_18.0', 'heatingorsystemtypeid_10.0', 'propertylandusetypeid_260', 'propertylandusecypeid_260', 'propertylandusecypeid_260', 'propertylandusecypeid_260', 'propertylandusecypeid_260', 'propertylandusecypeid_260', 'propertylandusecypeid_260', 'propertylandusecypeid_260', 'propertylandusecypeid_260', 'propertylandusetypeid_260', 'propertylandusetypeid_260', 'propertylandusetypeid_260', 'propertylandusetypeid_260', 'propertylandusetypeid_265.0', 'propertylandusetypeid_267.0', 'propertylandusetypeid_267.0', 'propertylanduset
[27]:	inishedograpere feet[2], 'firenlocoent', 'latitude', 'longitude', 'longitude', 'longitude', 'regionidety', 'regionidety', 'regionidety', 'regionidety', 'regionidety', 'regionidety', 'period', 'regionidety', 'regionidety', 'period', 'regionidety', 'period', 'regionidety', 'period', 'regionidety', 'landicaveludedilacum', 'landicaveludedilacum
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	propertylandusetypeid_24.0 heatingorsystemtypeid_24.0 propertycountylandusecode_0100 propertyzoningdesc_LAR1 heatingorsystemtypeid_1.0 propertycountylandusecode_34 propertycountylandusecode_122 fips_6037.0 propertylandusetypeid_260.0 propertylandusetypeid_6.0 heatingorsystemtypeid_11.0 heatingorsystemtypeid_12.0 propertylandusetypeid_248.0 heatingorsystemtypeid_13.0 heatingorsystemtypeid_18.0 fips_6111.0 heatingorsystemtypeid_2.0 propertylandusetypeid_2.0 propertylandusetypeid_3.0 heatingorsystemtypeid_3.0 heatingorsystemtypeid_3.0 heatingorsystemtypeid_3.0 propertyzoningdesc_LAR3 propertyzoningdesc_LBR1N heatingorsystemtypeid_10.0
	heatingorsystemtypeid_10.0 propertylandusetypeid_264.0 buildingqualitytypeid heatingorsystemtypeid_20.0 propertycountylandusecode_rare fips_6059.0 propertylandusetypeid_269.0 propertylandusetypeid_247.0 propertyzoningdesc_rare unitcnt_na_flag propertylandusetypeid_263.0 propertylandusetypeid_31.0 propertyzoningdesc_LARS propertyzoningdesc_LARS propertycountylandusecode_010C heatingorsystemtypeid_7.0 propertyzonitylandusecode_0101 buildingqualitytypeid_na_flag (37)
In [36]:	Terza Contea 3101  print_list_info(to_delete[2])  propertylandusetypeid_267.0 heatingorsystemtypeid_24.0 heatingorsystemtypeid_265.0 propertylandusetypeid_265.0 propertylandusetypeid_266.0 propertycountylandusecode_34 propertycountylandusecode_122 fips_6037.0 propertylandusetypeid_260.0 propertylandusetypeid_260.0 propertylandusetypeid_260.0 propertysoningdesc_LARD1.5 poolent_1.0 heatingorsystemtypeid_6.0 heatingorsystemtypeid_11.0 heatingorsystemtypeid_12.0 propertylandusetypeid_248.0 heatingorsystemtypeid_13.0 heatingorsystemtypeid_13.0 heatingorsystemtypeid_18.0 propertylandusetypeid_275.0 fips_6111.0 propertylandusetypeid_275.0 fips_6111.0 propertyzoningdesc_LAR3
	propertyzoningdesc_LBRIN heatingorsystemtypeid_10.0 propertylandusetypeid_264.0 heatingorsystemtypeid_20.0 fips_6059.0 propertylandusetypeid_269.0 propertylandusetypeid_247.0 unitcnt_na_flag propertylandusetypeid_263.0 propertylandusetypeid_31.0 propertylandusetypeid_31.0 propertyzoningdesc_LARS propertyzoningdesc_LARS propertycountylandusecode_010C rooment fireplaceent propertylandusetypeid_261.0 buildingqualitytypeid_na_flag (36)  Sembra che principalmente siano eliminate la maggior parte delle colonne generate dal One-Hot Encoding, queste sembrano avere scarsa importanza come evidenziava anche la prima analisi legata al ranking di una foresta.
In [37]: In [38]:	<pre>def remove_column(df, col_names):     df.drop(col_names, axis=1, inplace=True)     return df</pre>
In [39]: In [40]:	for X in [X_train[i], X_val[i], X_test[i]]:
In [41]:	<pre>X_valC: (21908, 33) X_testC: (21876, 33) Y_trainC: (64771, 1) Y_valC: (21908, 1) Y_valC: (21908, 1) Y_testC: (21876, 1)  Analisi dei risultati Il nuemero di feature selezionate è analogo a quello ottenuto dall'increasing RMSE: una cinquantina di feature per la prima contea e una trentina per la seconda e la terza. Analisi delle feature comuni.  Feature selezionate comuni a tutte e tre le contee:  common = set(X_train[0].columns) for i in range(1,3):     common = common.intersection(set(X_train[i].columns)) common = list(common)</pre>
	print_list_info(common)  taxvaluedollarcnt latitude structuretaxvaluedollarcnt tax_prop finishedsquarefeet12 rawcensustractandblock regionidcity yearbuilt bedrooment lotsizesquarefeet propertylandusetypeid_246.0 assessmentyear_2015.0 taxamount longitude calculatedfinishedsquarefeet unitcnt living_area_prop bathrooment neighborhood_mean_price int_transactiondate landtaxvaluedollarcnt calculateddatnhr period_mean_price tax_ratio regionidzip
In [42]:	<pre>for i in range(3):     X_train[i].to_csv( dir_name + f'/X_train{region_names[i]}.csv', index=False)     X val [i].to csv( dir_name + f'/X val{ region_names[i]}.csv', index=False)</pre>
	<pre>X_test [i].to_csv( dir_name + f'/X_test{ region_names[i]}.csv', index=False) y_train[i].to_csv( dir_name + f'/y_train{region_names[i]}.csv', index=False) y_val [i].to_csv( dir_name + f'/y_val{ region_names[i]}.csv', index=False) y_test [i].to_csv( dir_name + f'/y_test{ region_names[i]}.csv', index=False)</pre>