In [22]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.metrics import r2_score
from sklearn.linear_model import SGDRegressor, LassoCV
from sklearn.tree import DecisionTreeRegressor
from sklearn.feature_selection import mutual_info_regression, SelectKBest
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
import joblib
```

Exploratory Data Analysis and Model Building

In [23]:
```
df = pd.read_csv('static/2023_01_to_04.csv', index_col=0)
display(df.head())
print(df.shape)
```

	resale_price	year	month	timeseries_month	region	town	rooms	avg_storey	floor_area_sqm	remainii
_id										
150071	298000.0	2023	4	2023-04-01	North-East	Ang Mo Kio	2.0	8.0	44.0	5:
152255	865000.0	2023	4	2023-04-01	North	Yishun	5.5	11.0	142.0	6:
152254	780000.0	2023	4	2023-04-01	North	Yishun	5.5	11.0	142.0	6:
152253	935000.0	2023	4	2023-04-01	North	Yishun	5.5	5.0	164.0	6{
152252	892000.0	2023	4	2023-04-01	North	Yishun	5.5	2.0	169.0	6{

```
(8859, 15)
```

1. EDA

Summary of actions before training

1. Handling null values and Checking for collinearity
2. Preprocessing (mean encoding)
3. Feature selection (KBest, Lasso regression)
4. Model selection
5. Hyperparameter tuning

1.1 Handling null values

In [25]:
```
#display(df[df['dist_to_station'].isna()])
df.dropna(inplace=True)
```

In [26]:
```
display(df.isna().sum())
```

```
resale_price         0
year                 0
month                0
timeseries_month     0
region               0
town                 0
rooms                0
avg_storey           0
floor_area_sqm       0
remaining_lease      0
dist_to_marina_bay   0
latitude             0
longitude            0
nearest_station_0    0
dist_to_station0     0
dtype: int64
```

Explanation for each feature

Feature*	Explanation
resale_price	Dependent variable, the selling price of the flat
region	Region of the flat
town	Town district of the flat
rooms	Number of rooms in the flat (whole numbers except for 5.5, which represents an executive flat with an extra study/balcony)
avg_storey	Mean value of the floor range (intervals of 3 storeys)
floor_area_sqm	Total floor area (in square meters) of the flat
remaining_lease	Remaining lease of the flat in months
dist_to_marina_bay	Distance in absolute coordinates to Marina Bay (proxy to city center)
dist_to_station	Distance in meters to the nearest MRT (Mass Rapid Transit) station
min_pt_time	Time in seconds to reach the nearest MRT station by public transport and walking

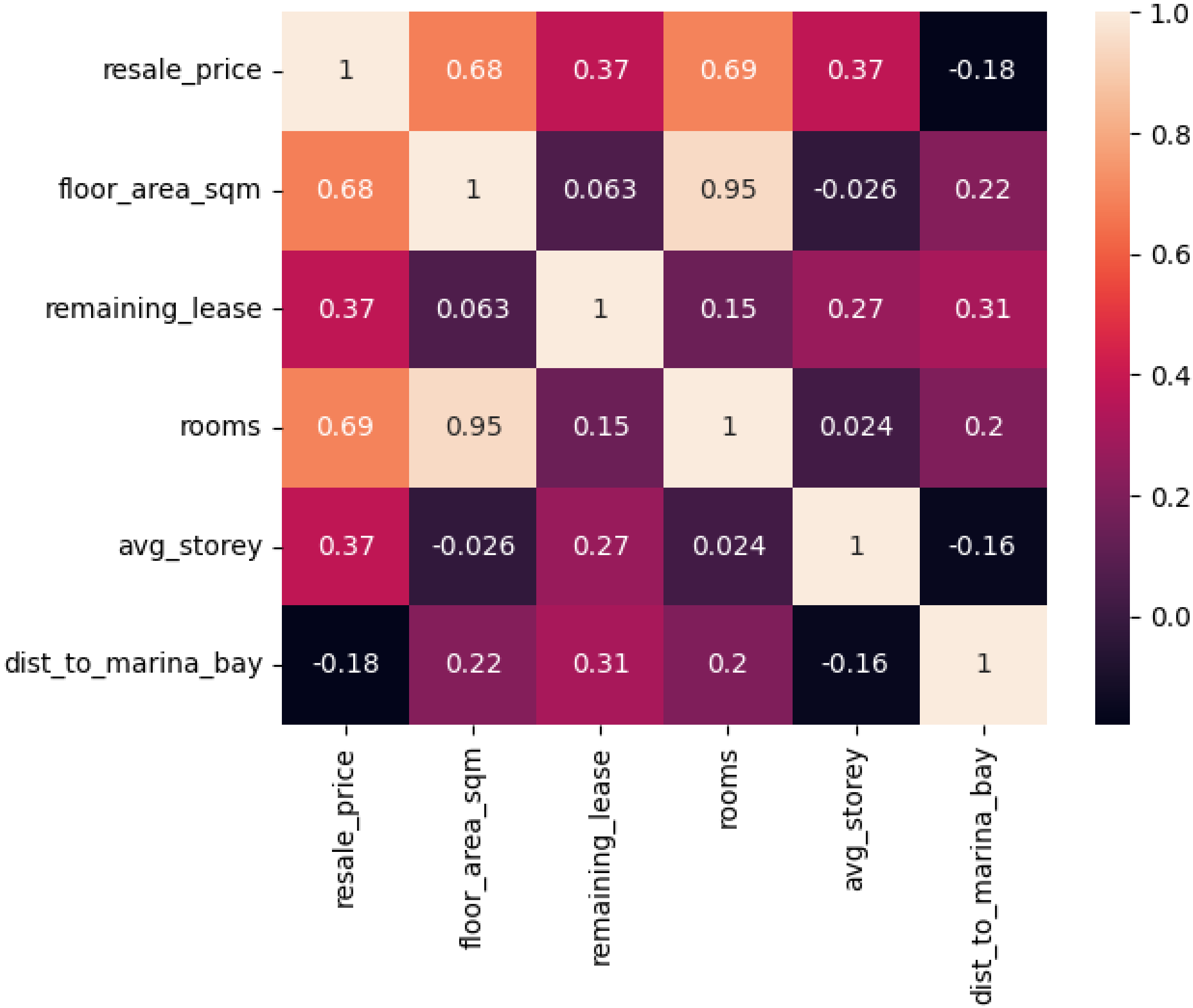
*Other features not listed above but in DataFrame are for visual plotting purposes

1.1 Checking for collinearity among numerical features

- There is strong collinearity between
  - floor_area_sqm and rooms (0.86)
  - dist_to_station and min_pt_time (0.69)
- Even much so higher than their correlation with output (resale price)
- For linear models, we need to remove one of each pair of feature to ensure that there is no multicollinearity, for this I will remove the feature with lower Pearson's correlation with our output
  - rooms (0.65)
  - min_pt_time (0.69)

In [27]:
```python
numerical_columns = df[['resale_price', 'floor_area_sqm', 'remaining_lease', 'rooms', 'avg_store
sns.heatmap(numerical_columns.corr(), annot=True)
```

Out[27]:
```
<Axes: >
```



What are the most expensive neighbourhoods?

Each neighbourhood has a different mean price due to a non-exhaustive number of factors:

- location
- infrastructure and amenitites
- affluent / less affluent neighbourhoods
- supply and demand
- market speculation

In [28]:
```
region_prices = df.groupby(['region', 'rooms'])[['resale_price']].median(numeric_only=True).sort
region_prices = region_prices.unstack()
region_prices.columns = ['1 room', '2 room', '3 room', '4 room', '5 room', 'Executive', 'Mansion
region_prices.style.format(precision=0, thousands=',').highlight_max(color='red').highlight_min(
```

Out[28]:

region	1 room	2 room	3 room	4 room	5 room	Executive	Mansionette
Central	238,500	270,000	385,000	755,000	885,000	1,030,000	nan
East	nan	346,500	389,444	542,000	656,500	840,000	nan
North	nan	322,000	387,500	490,000	600,000	768,000	1,080,000
North-East	nan	330,000	406,500	560,888	650,000	820,000	nan
West	nan	320,000	375,000	500,000	619,000	750,000	nan

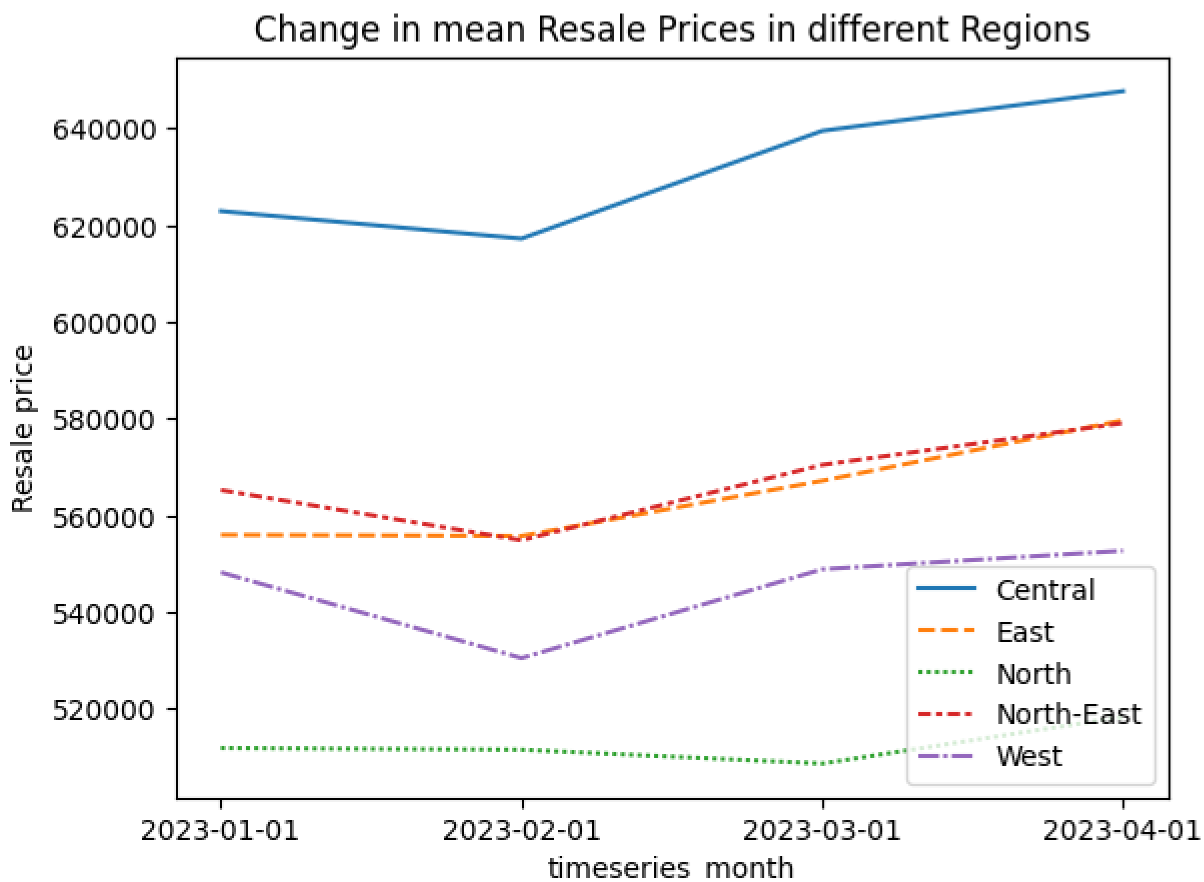
In [29]:
```
town_prices = df.groupby(['town', 'rooms'])[['resale_price']].median(numeric_only=True).sort_val
town_prices = town_prices.unstack()
town_prices.columns = ['1 room', '2 room', '3 room', '4 room', '5 room', 'Executive', 'Mansionet
town_prices.style.format(precision=0, thousands=',').highlight_max(color='red').highlight_min(co
```

Out[29]:

town	1 room	2 room	3 room	4 room	5 room	Executive	Mansionette
Ang Mo Kio	nan	289,900	380,000	560,000	780,000	933,000	nan
Bedok	nan	285,000	365,000	490,000	660,000	870,000	nan
Bishan	nan	nan	460,000	685,000	900,000	1,050,000	nan
Bukit Batok	nan	339,000	370,000	590,000	760,000	820,000	nan
Bukit Merah	238,500	270,000	394,000	815,000	870,000	nan	nan
Bukit Panjang	nan	302,500	380,500	490,000	620,000	796,888	nan
Bukit Timah	nan	nan	465,000	777,500	985,000	1,288,000	nan
Central Area	nan	328,000	447,400	884,000	1,340,000	nan	nan
Choa Chu Kang	nan	307,500	411,500	490,000	582,000	715,000	nan
Clementi	nan	nan	419,000	620,000	761,500	955,000	nan
Geylang	nan	256,000	339,500	555,000	712,500	928,000	nan
Hougang	nan	330,000	385,000	519,000	670,000	850,000	nan
Jurong East	nan	311,500	363,000	470,000	658,000	780,000	nan
Jurong West	nan	296,000	345,000	475,000	585,000	692,500	nan
Kallang/Whampoa	nan	283,000	380,000	732,500	805,000	962,800	nan
Marine Parade	nan	nan	436,888	577,500	841,500	nan	nan
Pasir Ris	nan	360,000	520,000	535,000	645,000	810,000	nan
Punggol	nan	335,000	450,000	582,000	668,000	698,000	nan
Queenstown	nan	261,944	405,944	860,000	976,500	1,190,000	nan
Sembawang	nan	325,000	438,500	535,000	576,500	650,000	nan
Sengkang	nan	335,944	443,000	560,000	608,000	733,888	nan
Serangoon	nan	nan	390,000	585,000	660,000	900,000	nan
Tampines	nan	337,500	416,000	560,000	670,000	859,444	nan
Toa Payoh	nan	258,444	353,500	724,000	915,000	1,018,000	nan
Woodlands	nan	320,000	390,000	484,000	585,000	772,500	nan
Yishun	nan	315,000	378,000	480,000	636,500	800,000	1,080,000

Change in resale prices within year 2023

In [30]:
```
ma_df = df.groupby(['timeseries_month', 'region'])['resale_price'].mean()
ma_df = ma_df.unstack()
sns.lineplot(ma_df)
plt.title('Change in mean Resale Prices in different Regions')
plt.ylabel('Resale price')
plt.legend(loc='lower right')
plt.show()
```



1.2 Preprocessing (mean and label encoding)

- I will perform mean encoding (resale_price) onto the town and rooms.
- Take note that mean encoding may sometimes result in overfitting.

In [31]:

```
# Label encoding for town
encoder = LabelEncoder()
town_label = pd.Series(encoder.fit_transform(df['town']), name='town_encoded', index=df.index)

# Label encoding for region
region_label = pd.Series(encoder.fit_transform(df['region']), name='region_encoded', index=df.in
```

Custom class for Mean/Median encoding

In [32]:

```
class MeanEncoder():
    '''
    Custom class encoder to deal with mean/median encoding
    '''
    def __init__(self, measure:str='mean'):
        self.encoder_dict_ = None
        self.columns_ = None
        self.measure_ = measure
        self.target_column_ = None

    def fit(self, X : pd.DataFrame, columns : list, target_column : str)->None:
        '''
        Fit to dataframe to create encoder_dict_ (dictionary) for data mapping
        ## Parameters
            X : pd.DataFrame object
            columns : list of strings, indicating columns to groupby
            target_column : str, desired output (must be numeric)
        Returns None
```

```
        '''
        self.columns_ = columns
        self.target_column_ = target_column
        if self.measure_ == 'mean':
            self.encoder_dict_ = X.groupby(self.columns_)[self.target_column_].mean(numeric_only
        elif self.measure_ == 'median':
            self.encoder_dict_ = X.groupby(self.columns_)[self.target_column_].median(numeric_on

    def transform(self, X : pd.DataFrame)->pd.Series:
        '''
        Transform dataframe by mapping data using encoder_dict_
        ## Parameters
            X : pd.DataFrame object
        Returns pd.Series of encoded data
        '''
        def columns_to_tuple(df, columns):
            '''
            Function to combined columns as a tuple for dictionary mapping
            '''
            temp = []
            for column in columns:
                temp.append(df[column])
            return tuple(temp)

        row_tuple = X.apply(columns_to_tuple, columns = self.columns_, axis=1)
        row_tuple.name = f'{self.measure_}_encoded'
        output =  row_tuple.map(self.encoder_dict_)
        return output
```

In [33]:

```
#  Median encoding on towns and rooms
median_encoder = MeanEncoder(measure='median')
median_encoder.fit(df, columns=['town', 'rooms'], target_column='resale_price')
town_median_price = median_encoder.transform(df)

#  Mean encoding on towns and rooms
mean_encoder = MeanEncoder(measure='mean')
mean_encoder.fit(df, columns=['town', 'rooms'], target_column='resale_price')
town_mean_price = mean_encoder.transform(df)

train_df = pd.concat([numerical_columns, town_median_price, town_mean_price, town_label, region_
train_df.head()
```

Out[33]:

_id	resale_price	floor_area_sqm	remaining_lease	rooms	avg_storey	dist_to_marina_bay	median_encoded	m
150071	298000.0	44.0	53.750000	2.0	8.0	9.23	289900.0	2
152255	865000.0	142.0	63.833333	5.5	11.0	14.89	800000.0	8
152254	780000.0	142.0	62.166667	5.5	11.0	16.13	800000.0	8
152253	935000.0	164.0	68.166667	5.5	5.0	15.54	800000.0	8
152252	892000.0	169.0	68.333333	5.5	2.0	17.08	800000.0	8

1.3 Feature selection

In [34]:

```
X_unscaled = train_df.iloc[:,1:]
y = train_df.iloc[:,0]
scaler = MinMaxScaler()
```

```
X = scaler.fit_transform(X_unscaled)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

SelectKBest using Mutual Information

In [35]:
```
X_df = pd.DataFrame(X, columns=X_unscaled.columns)
kbest = SelectKBest(score_func=mutual_info_regression, k='all')
kbest.fit(X_df, y)
pd.DataFrame(kbest.scores_, index=kbest.get_feature_names_out(kbest.feature_names_in_), columns=
```

Out[35]:

	Mutual Info Score
floor_area_sqm	0.732128
remaining_lease	0.329396
rooms	0.532034
avg_storey	0.088830
dist_to_marina_bay	0.251546
median_encoded	0.868921
mean_encoded	0.888959
town_encoded	0.211584
region_encoded	0.103505

Lasso regularisation to determine less important features

In [36]:
```
# LassoCV here uses crossvalidation to determine the optimum alpha (penalty value)
lr_reg1 = LassoCV(random_state=42)
lr_reg1.fit(X_train, y_train)
r2 = r2_score(y_test, lr_reg1.predict(X_test))
print(f'LassoCV Alpha: {np.round(lr_reg1.alpha_,3)}')
print(f'R2 score: {np.round(r2,3)}')
print()
print('Scaled weights for comparison')

feature_scaler = MinMaxScaler()
scaled_f_importances = feature_scaler.fit_transform(lr_reg1.coef_.reshape(-1,1))
display(pd.DataFrame(scaled_f_importances, index=X_unscaled.columns, columns=['Features']))
```

```
LassoCV Alpha: 20.221
R2 score: 0.883

Scaled weights for comparison
```

	Features
floor_area_sqm	0.998547
remaining_lease	0.505232
rooms	0.000000
avg_storey	0.519582
dist_to_marina_bay	0.119416
median_encoded	0.179666
mean_encoded	1.000000
town_encoded	0.254826
region_encoded	0.242575

Final selection of features

Based on the EDA, KBest and LassoCV done so far, the following features will be excluded:

- rooms (to utilise in mean encoding instead)
- dist_to_station
- median_encoded
- town_encoded
- region_encoded

Mean encoding works the best, hence we will not consider the label encoded features and median encoded prices.

In [37]:
```
X_unscaled = train_df[['floor_area_sqm', 'remaining_lease', 'avg_storey', 'dist_to_marina_bay',
y = train_df.iloc[:,0]
scaler = MinMaxScaler()
X = scaler.fit_transform(X_unscaled)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

1.4 Model Selection

We will compare the following models in general, before hyperparameter tuning

- SGD Regressor
- Decision Tree Regressor
- Random Forest Regressor
- Gradient Boosting Regressor

In [38]:
```
models = {'SGD Regressor' : SGDRegressor(random_state=42),
          'Tree Regressor' : DecisionTreeRegressor(random_state=42),
          'Random Forest Regressor' : RandomForestRegressor(random_state=42),
          'Gradient Boosting Regressor' : GradientBoostingRegressor(random_state=42)}

for name, model in models.items():
    model.fit(X_train, y_train)
    r2 = r2_score(y_test, model.predict(X_test))
    print(f'R2 score for {name}: {np.round(r2,3)}')
```

```
R2 score for SGD Regressor: 0.876
R2 score for Tree Regressor: 0.913
R2 score for Random Forest Regressor: 0.948
R2 score for Gradient Boosting Regressor: 0.928
```

In [39]:
```
feature_importances = {}
for name, model in models.items():
    if name == 'SGD Regressor':
        continue
    feature_importances[name]= model.feature_importances_

print('Feature Importances')
display(pd.DataFrame(feature_importances, index=X_unscaled.columns))
```

```
Feature Importances
```

	Tree Regressor	Random Forest Regressor	Gradient Boosting Regressor
floor_area_sqm	0.173493	0.163612	0.106318
remaining_lease	0.142669	0.132366	0.136929
avg_storey	0.026634	0.031707	0.037626
dist_to_marina_bay	0.067113	0.065049	0.039756
mean_encoded	0.590092	0.607266	0.679371

New ideas

In [40]:
```
# Add permutation importances
# impurity-based importances are biased towards high cardinality features
# min_samples_leaf in gridsearch
# plot out tree to see if overfitted
```

The ensemble models (Random Forest and Gradient Boosting) tend to perform better. I will narrow down to tune these two models for now.

1.5 Hyperparameter tuning

Randomized Search Cross-Validation to tune the hyperpameters for the top 2 models

Random Forest Regressor

In [41]:
```
param_distributions = {'max_depth' : [None, 3,5,7,9],
                       'n_estimators' : [50,100,150],
                       'min_samples_leaf' : [50, 100, 150]
                       }

random_cv = RandomizedSearchCV(estimator=RandomForestRegressor(random_state=42),
                               scoring= 'r2',
                               param_distributions= param_distributions,
                               n_iter= 15,
                               cv= 5,
                               verbose= 1,
                               n_jobs=2)

random_cv.fit(X, y)
print('Best Parameters', random_cv.best_params_)
```

```
print('Best R2 score', np.round(random_cv.best_score_,3))
best_rfr = random_cv.best_estimator_
```

```
Fitting 5 folds for each of 15 candidates, totalling 75 fits
Best Parameters {'n_estimators': 50, 'min_samples_leaf': 50, 'max_depth': 7}
Best R2 score 0.882
```

Gradient Boosting Regressor

In [42]:
```
param_distributions = {'max_depth' : [None, 3,5,7,9],
                       'n_estimators' : [50,100,150],
                       'learning_rate' : [0.01,0.1,1]
                       }

random_cv = RandomizedSearchCV(estimator=GradientBoostingRegressor(random_state=42),
                               scoring= 'r2',
                               param_distributions= param_distributions,
                               n_iter= 15,
                               cv= 5,
                               verbose= 1,
                               n_jobs=2)

random_cv.fit(X, y)
print('Best Parameters', random_cv.best_params_)
print('Best R2 score', np.round(random_cv.best_score_,3))
best_gbc = random_cv.best_estimator_
```

```
Fitting 5 folds for each of 15 candidates, totalling 75 fits
Best Parameters {'n_estimators': 50, 'max_depth': 9, 'learning_rate': 0.1}
Best R2 score 0.945
```

Test on subsequent month's data (Unseen)

In [44]:
```
test_df = pd.read_csv('static/2023_05.csv', index_col=0)

# Use previous dictionary of the town and rooms for mean encoding
mean_encoded = mean_encoder.transform(test_df)
test_df = pd.concat([test_df, mean_encoded], axis =1)
test_df = test_df[['resale_price','floor_area_sqm', 'remaining_lease', 'avg_storey', 'dist_to_ma
display(test_df.head())
print(test_df.shape)
```

_id	resale_price	floor_area_sqm	remaining_lease	avg_storey	dist_to_marina_bay	mean_encoded
152256	275000.0	44.0	53.75	2.0	9.23	293168.800000
152257	300000.0	45.0	61.75	8.0	10.45	293168.800000
152258	348000.0	67.0	53.75	11.0	9.62	399997.149425
152259	330000.0	68.0	56.75	2.0	10.17	399997.149425
152260	400000.0	67.0	54.75	8.0	9.38	399997.149425

```
(2063, 6)
```

In [45]:
```
X_test = test_df.iloc[:,1:]
y_test = test_df.iloc[:,0]
X_test = scaler.transform(X_test)

r2 = r2_score(y_test, best_rfr.predict(X_test))
print(f'R2 score for Random Forest Regressor: {np.round(r2,3)}')
```

```
r2 = r2_score(y_test, best_gbc.predict(X_test))
print(f'R2 score for Gradient Boosting Regressor: {np.round(r2,3)}')
```

```
R2 score for Random Forest Regressor: 0.877
R2 score for Gradient Boosting Regressor: 0.947
```

In [46]:
```
# Plot r2 graphs
y_pred = best_rfr.predict(X_test)
plt.scatter(y_test, y_pred , marker='.', s=2)
plt.xlabel('Actual values')
plt.ylabel('Predicted values')
plt.plot([0,max(y_test)], [0, max(y_pred)])
plt.title('R2 plot for Random Forest Regressor')
plt.show()
```

In [47]:
```
# Plot r2 graphs
y_pred = best_gbc.predict(X_test)
plt.scatter(y_test, y_pred , marker='.', s=2)
plt.xlabel('Actual values')
plt.ylabel('Predicted values')
plt.plot([0,max(y_test)], [0, max(y_pred)])
plt.title('R2 plot for Gradient Boosting Regressor')
plt.show()
```

Exporting the objects for deployment

In [49]:
```
print(joblib.dump(scaler, 'models/scaler.joblib'))
print(joblib.dump(mean_encoder, 'models/mean_encoder.joblib'))
```

```
['models/scaler.joblib']
['models/mean_encoder.joblib']
```
Out[49]:

In [129…
```
name = input(f'Name save file for model {best_gbc}\n')
if name != '':
    filepath = f'models/gbc_{name}.joblib'
    joblib.dump(best_gbc, filepath)
    print(f'File saved as {filepath}')

name = input(f'Name save file for model {best_rfr}\n')
if name != '':
    filepath = f'models/rfr_{name}.joblib'
    joblib.dump(best_rfr, filepath)
    print(f'File saved as {filepath}')
```

```
File saved as models/gbc_2023_01_to_04.joblib
File saved as models/rfr_2023_01_to_04.joblib
```