ExoClick_Challenge_Solution

October 20, 2018

0.1 Exploratory Data Analysis

```
In [18]: import pandas as pd

         # reading csv as a dataframe
         df = pd.read_csv('ExoClick_challenge.csv')
         print('Shape of data:',df.shape)
         print('Shape of data if missing values are to be dropped:', df.dropna().shape)
```

```
('Shape of data:', (96223, 6))
('Shape of data if missing values are to be dropped:', (96213, 6))
```

```
In [19]: # Finding the unique values; Data Pre-Processing in case of redundancy;
         print('Unique countries:',df['country'].unique())
         print('Unique ad_type:',df['ad_type'].unique(), '\n')

         # Check for missing data
         print('Checking for attribute with missing values: \n',df.isna().any())
```

```
('Unique countries:', array(['EST', 'NCL', 'DZA', 'ISL', 'isl', 'dza', 'est', 'ncl'],
      dtype=object))
('Unique ad_type:', array([10, 17,  2, 15]), '\n')
('Checking for attribute with missing values: \n', dattime        False
client         False
country        False
ad_type        False
impressions    False
value           True
dtype: bool)
```

```
In [20]: # dropping missing values as insignificant number of them are present
         df = df.dropna()
         print('Dataframe view after removing missing values\n',df.head(5))

         # rows with redundant country codes
         print('\n','Rows with redundant Country Codes')
```

```
print(df[df['country']=='isl'])
print(df[df['country']=='dza'])
print(df[df['country']=='est'])
print(df[df['country']=='ncl'])
```

```
('Dataframe view after removing missing values\n',                dattime  client country  ad_t
0  2016-06-06*06:00:00       1     EST       10          137   0.1370
1  2016-06-12*22:00:00       2     NCL       10         4424  91.7207
2  2016-06-05*20:00:00       1     DZA       10          271   0.2710
3  2016-06-23*17:00:00       1     EST       17            1   0.0010
4  2016-06-02*10:00:00       3     DZA       10        11701   4.8719)
('\n', 'Rows with redundant Country Codes')
                   dattime  client country  ad_type  impressions   value
624    2016-06-16*07:00:00       9     isl        2           89  0.4894
6397   2016-06-03*23:00:00      25     isl        2          129  0.6450
15119  2016-06-11*10:00:00       3     isl       17            7  0.0049
30699  2016-06-01*14:00:00      13     isl        2           94  0.0000
                   dattime  client country  ad_type  impressions   value
768    2016-06-25*14:00:00      23     dza        2          359  4.7194
79898  2016-06-29*06:00:00       3     dza       10         1439  0.8040
                   dattime  client country  ad_type  impressions   value
17855  2016-06-03*05:00:00      38     est        2           34  0.3554
27891  2016-06-06*10:00:00      52     est        2            5  0.0250
61551  2016-06-28*17:00:00       9     est        2          580  2.9085
                   dattime  client country  ad_type  impressions  value
61833  2016-06-09*09:00:00       5     ncl       10          101   1.01
```

In [21]:
```
# converting the countries with lower case to upper case
row_numbers_to_process = []
row_numbers_to_process.extend(df[df['country']=='isl'].index)
row_numbers_to_process.extend(df[df['country']=='dza'].index)
row_numbers_to_process.extend(df[df['country']=='est'].index)
row_numbers_to_process.extend(df[df['country']=='ncl'].index)

for num in row_numbers_to_process:
    df.loc[num,'country'] = df.loc[num,'country'].upper()

print('Unique Countries after Processing:', df['country'].unique())
```

```
('Unique Countries after Processing:', array(['EST', 'NCL', 'DZA', 'ISL'], dtype=object))
```

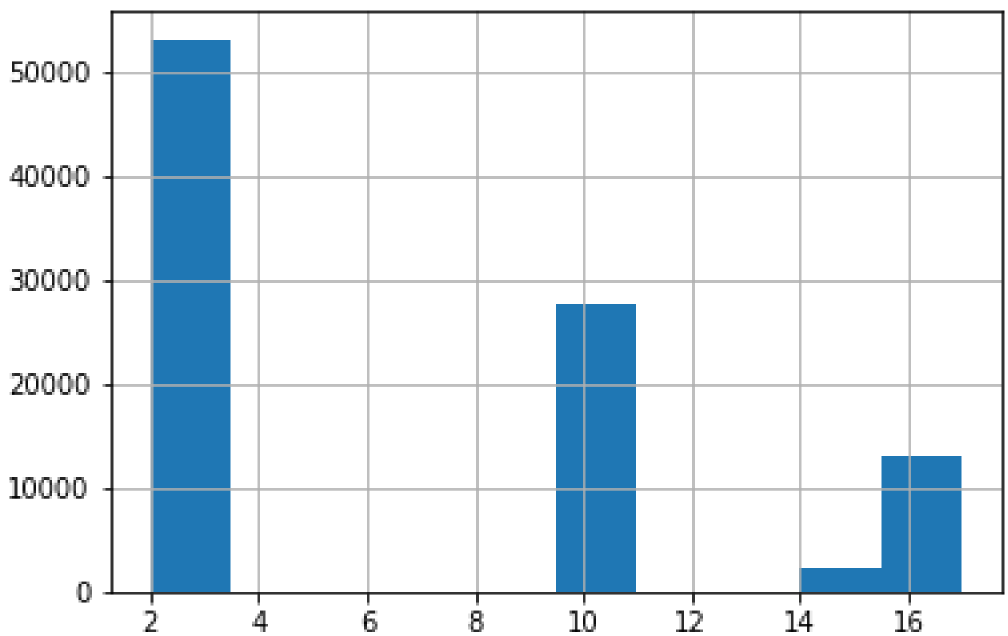
In [22]:
```
# computing summary statistics
print('Shape of Dataset',df.shape)
print(df.describe())
```

```
('Shape of Dataset', (96213, 6))
             client       ad_type    impressions         value
```

count	96213.000000	96213.000000	96213.000000	96213.000000
mean	16.665004	6.642190	4045.791535	4.002480
std	14.327285	5.593171	31902.587268	15.084129
min	1.000000	2.000000	1.000000	0.000000
25%	4.000000	2.000000	7.000000	0.020100
50%	13.000000	2.000000	42.000000	0.140000
75%	25.000000	10.000000	379.000000	1.104600
max	73.000000	17.000000	941289.000000	846.000000

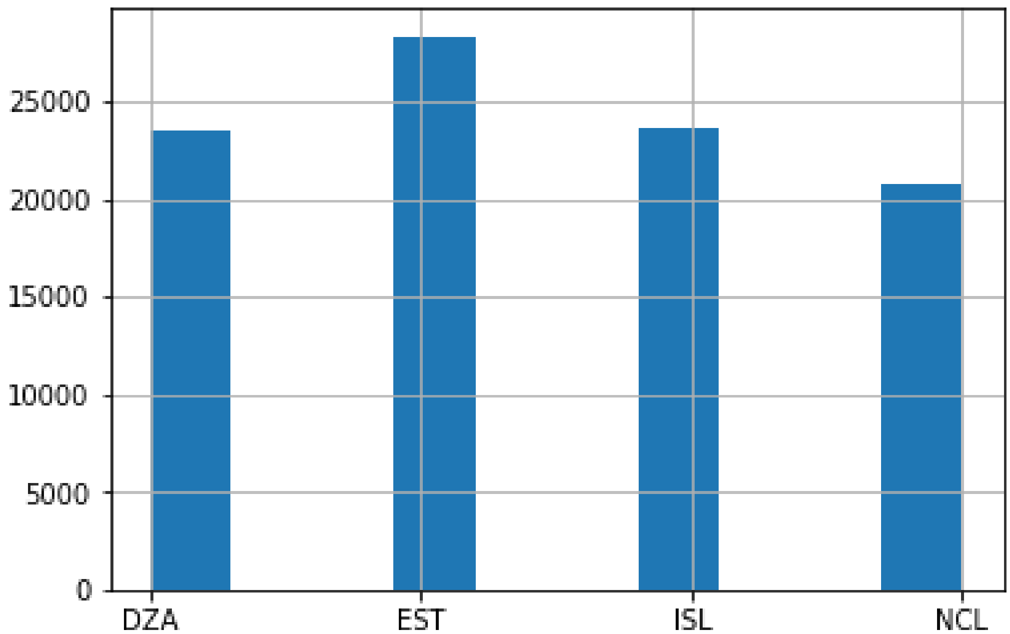
```
In [78]: print('Frequency of ad_types\n')
         df['ad_type'].hist();
```

Frequency of ad_types




```
In [81]: print('Country frequency')
         df['country'].hist();
```

Country frequency



0.2 Computing eCPM

In [82]:
```
# computing eCPM for each segment given by a country and ad_type
ecpm_df = df.groupby(['country', 'ad_type']).sum()
ecpm_df['eCPM'] = ''
ecpm_df['eCPM'] = (ecpm_df['value']*1000)/(ecpm_df['impressions'])
print(ecpm_df[['impressions','value','eCPM']])
```

```
                impressions        value       eCPM
country ad_type
DZA     2         209732533   64402.8197   0.307071
        10         99589395   49136.4866   0.493391
        15            36051      48.1423   1.335394
        17           288743     130.5920   0.452278
EST     2          30512420   85804.5274   2.812118
        10         14598906   40917.6501   2.802789
        15            22860      23.7174   1.037507
        17            83608     199.4982   2.386114
ISL     2          15694168   14342.6641   0.913885
        10          6366502   12074.8048   1.896615
        15             5117       6.6349   1.296639
        17            58403     104.9812   1.797531
NCL     2           7764619   66507.4754   8.565453
        10          4481430   51331.6085  11.454292
        15             5546      16.7132   3.013559
```

```
17              17440      42.2456    2.422339
```

This clearly allows us to infer that 'NCL' is the country with highest eCPM fr the ad_type 10. We can also draw some other concusions such as- - In almost all countries, ad_type 2 is having the highest impressions followed by ad_type 10 - The country 'NCL' shows significantly higher levels of eCPM values for all values of ad_type

```
In [24]: # creating a dataframe with separate rows for date and time for ease of dataprocessin
         date_time = pd.DataFrame(df['dattime'].str.split('*',1).tolist(),
                                                columns = ['date','time'])
         df['date'] = date_time['date']
         df['time'] = date_time['time']
         df = df.drop(['dattime'], axis=1)
         df = df[['date', 'time', 'client', 'country', 'ad_type', 'impressions', 'value']]
         df.head(5)
```

Out[24]:

	date	time	client	country	ad_type	impressions	value
0	2016-06-06	06:00:00	1	EST	10	137	0.1370
1	2016-06-12	22:00:00	2	NCL	10	4424	91.7207
2	2016-06-05	20:00:00	1	DZA	10	271	0.2710
3	2016-06-23	17:00:00	1	EST	17	1	0.0010
4	2016-06-02	10:00:00	3	DZA	10	11701	4.8719

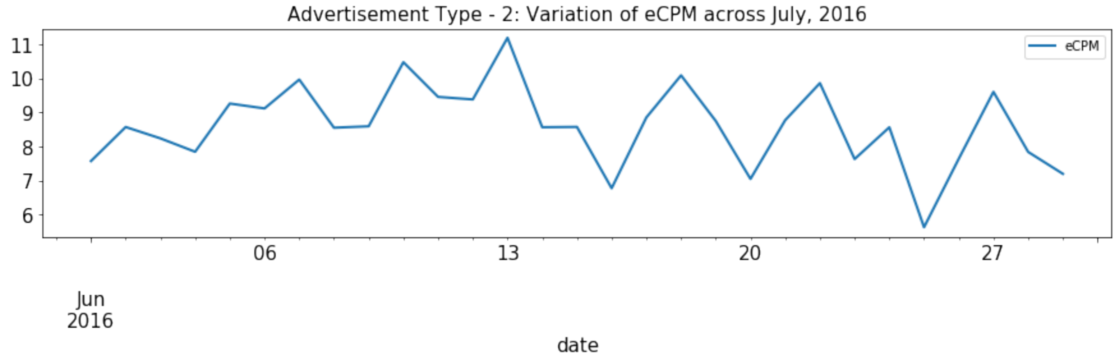
0.3 Daily Time Series

```
In [25]: import numpy as np
         import matplotlib.pyplot as plt
         %matplotlib inline
```

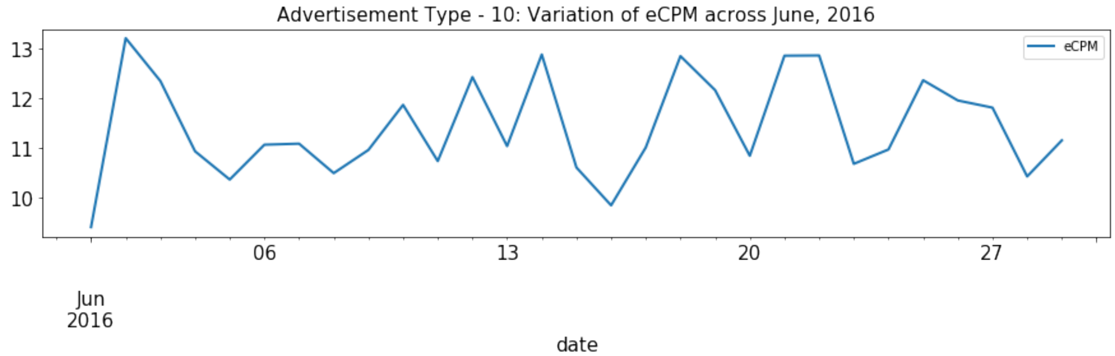
```
In [60]: # hourly time series including the dates
         NCL_df = df[df['country']=='NCL']
         NCL_df['date'] = pd.to_datetime(NCL_df['date'], format='%Y-%m-%d')
         NCL_df = NCL_df.drop(['time'], axis=1)
         NCL_df = NCL_df[['date', 'client', 'country', 'ad_type', 'impressions',
                          'value']]
         NCL_df = NCL_df.sort_values(by= ['date'])
         NCL_df = NCL_df.dropna()
         NCL_df = NCL_df.groupby(['ad_type', 'date']).sum()
         NCL_df['eCPM'] = ''
         NCL_df['eCPM'] = (NCL_df['value']*1000)/(NCL_df['impressions'])
         NCL_df = NCL_df.reset_index()
         NCL_df.set_index('date', inplace=True)
```

```
In [61]: # dataframes based on specific ad_types
         NCL_02_df = NCL_df[NCL_df['ad_type']== 2]
         NCL_10_df = NCL_df[NCL_df['ad_type']==10]
         NCL_15_df = NCL_df[NCL_df['ad_type']==15]
         NCL_17_df = NCL_df[NCL_df['ad_type']==17]
```

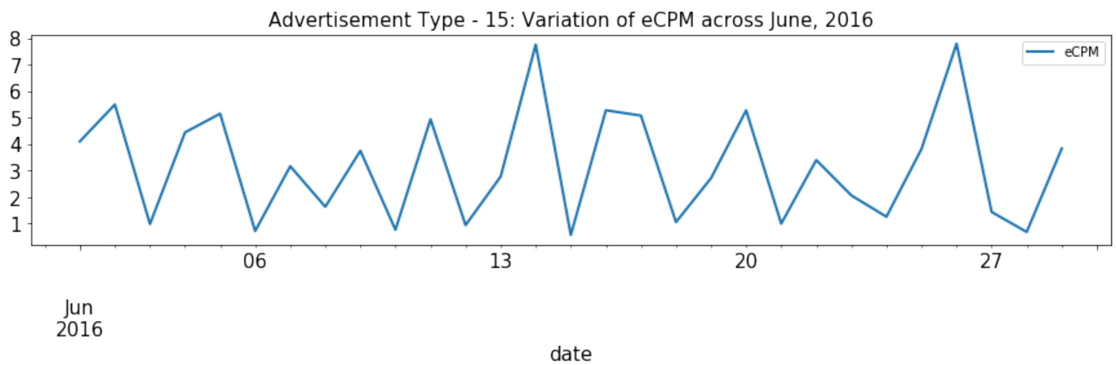
```
In [55]: NCL_02_df[['eCPM']].plot(figsize=(15,3), linewidth=2, fontsize=15)
         plt.xlabel('date', fontsize=15);
         plt.title('Advertisement Type - 2: Variation of eCPM across July, 2016', fontsize=15)
```



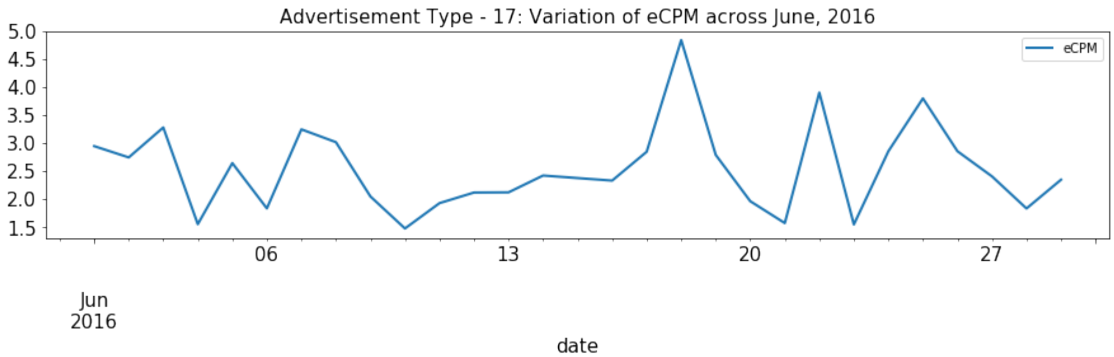

```
In [56]: NCL_10_df[['eCPM']].plot(figsize=(15,3), linewidth=2, fontsize=15)
         plt.xlabel('date', fontsize=15);
         plt.title('Advertisement Type - 10: Variation of eCPM across June, 2016', fontsize=15
```




```
In [57]: NCL_15_df[['eCPM']].plot(figsize=(15,3), linewidth=2, fontsize=15)
         plt.xlabel('date', fontsize=15);
         plt.title('Advertisement Type - 15: Variation of eCPM across June, 2016', fontsize=15
```



```
In [62]: NCL_17_df[['eCPM']].plot(figsize=(15,3), linewidth=2, fontsize=15)
         plt.xlabel('date', fontsize=15);
         plt.title('Advertisement Type - 17: Variation of eCPM across June, 2016', fontsize=15)
```



Clearly, we can draw certain conclusions from the information received so far from the specific ad_type time series plots regarding the variation of the metric eCMP. Some of them are listed below- * Advertisement Type 2- The highest value of eCPM occurs on 13th of June, 2016. Some relatively high values of the eCPM are also observed on 10th of June, 2016 and 18th of June, 2016. * Advertisement Type 10- The highest value of eCPM occurs on 2nd of June, 2016 * Advertisement Type 15- It has a more seasonal behaviour with crests and troughs occuring routinely. The highest value of eCPM is attained on 14th of June and 26th of June, 2016 * Advertisement Type 17- We can infer that the highest cost of eCPM arises on 18th of June, 2016 which continues to go through smaller crests and falls. The other important high values of eCPM occur on 3rd of June, 7th of June, 22nd of June, 25th of June

0.4 Hourly Time Series

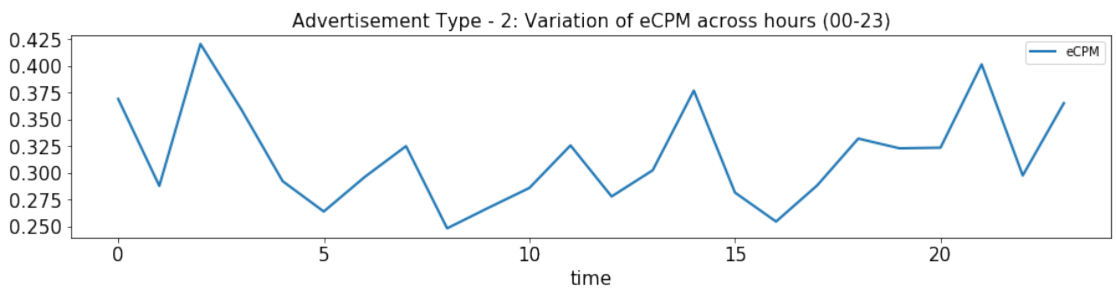
```
In [33]: import warnings
         import matplotlib.pyplot as plt
         warnings.filterwarnings('ignore')
```

```
In [34]: # hourly time series excluding the dates
         DZA_df = df[df['country']=='DZA']
         DZA_df['time'] = pd.to_datetime(DZA_df['time'], format='%H:%M:%S').dt.hour
         DZA_df = DZA_df.drop(['date'], axis=1)
         DZA_df = DZA_df[['time', 'client', 'country', 'ad_type', 'impressions',
                          'value']]
         DZA_df = DZA_df.sort_values(by= ['time'])
         DZA_df = DZA_df.dropna()
         DZA_df = DZA_df.groupby(['ad_type', 'time']).sum()
         DZA_df['eCPM'] = ''
         DZA_df['eCPM'] = (DZA_df['value']*1000)/(DZA_df['impressions'])
```

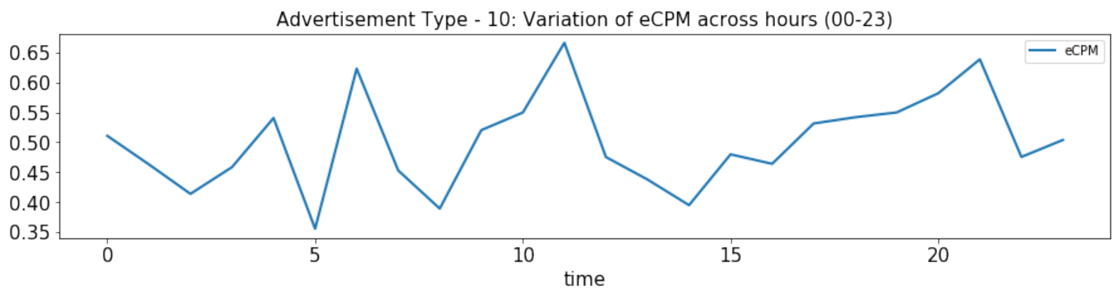
```
DZA_df = DZA_df.reset_index()
DZA_df.set_index('time', inplace=True)
```

In [35]:
```
# dataframes based on ad_types
DZA_02_df = DZA_df[DZA_df['ad_type']== 2]
DZA_10_df = DZA_df[DZA_df['ad_type']==10]
DZA_15_df = DZA_df[DZA_df['ad_type']==15]
DZA_17_df = DZA_df[DZA_df['ad_type']==17]
```

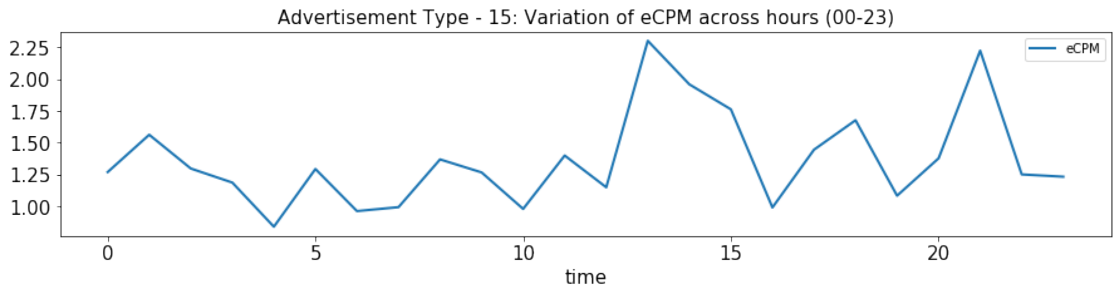
In [36]:
```
DZA_02_df[['eCPM']].plot.line(figsize=(15,3), linewidth=2, fontsize=15)
plt.xlabel('time', fontsize=15);
plt.title('Advertisement Type - 2: Variation of eCPM across hours (00-23)', fontsize=
```



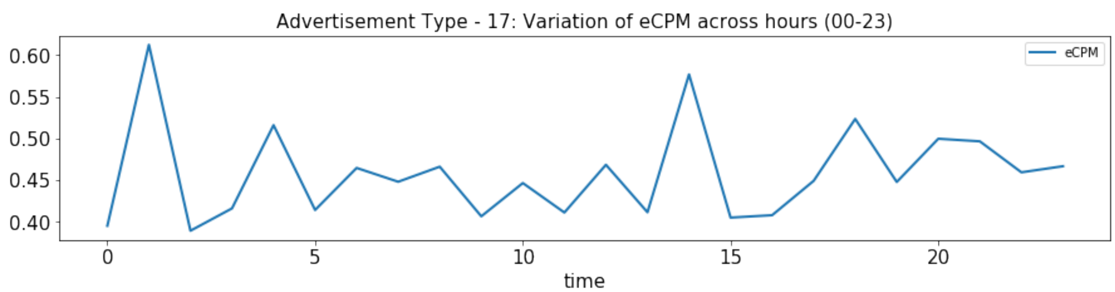
In [37]:
```
DZA_10_df[['eCPM']].plot.line(figsize=(15,3), linewidth=2, fontsize=15)
plt.xlabel('time', fontsize=15);
plt.title('Advertisement Type - 10: Variation of eCPM across hours (00-23)', fontsize
```



In [38]:
```
DZA_15_df[['eCPM']].plot.line(figsize=(15,3), linewidth=2, fontsize=15)
plt.xlabel('time', fontsize=15);
plt.title('Advertisement Type - 15: Variation of eCPM across hours (00-23)', fontsize
```




```
In [39]: DZA_17_df[['eCPM']].plot.line(figsize=(15,3), linewidth=2, fontsize=15)
         plt.xlabel('time', fontsize=15);
         plt.title('Advertisement Type - 17: Variation of eCPM across hours (00-23)', fontsize=
```



Clearly, we can draw certain conclusions from the information received so far from the specific ad_type time series plots regarding the variation of the metric eCMP. Some of them are listed below- * Advertisement Type 2- The highest value of eCPM is attained at 0200 hours in night. Some relatively high values of the eCPM are also achieved at 1400 hours and 2100 hours. * Advertisement Type 10- The highest value of eCPM is achieved at 1100 hours in the morning with comparatively smaller yet significantly high values attained also at 0600 hours in morning and 2100 hours in night * Advertisement Type 15- The highest value of eCPM is attained at 1300 hours in afternoon and 2100 hours in night * Advertisement Type 17- We can infer that the highest cost of eCPM arises at 0100 hours in night which continues to go through smaller crests and falls till it again reaches a significant high value at around 1400 hours in the afternoon.

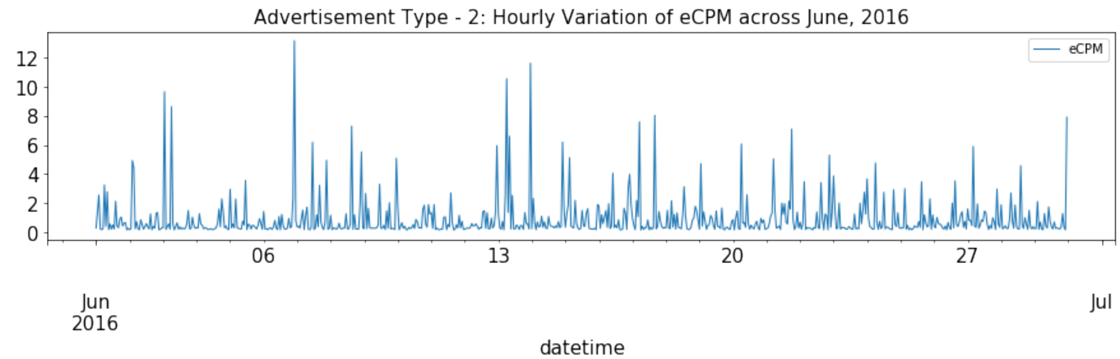
Now, we have decided to generate an overview of how the time series will look if both the date and time as unique factors will be retained and the dataframe sorted based on both the factors. The four plots following the 2 sections of code have implemented this feature

```
In [49]: # hourly time series including the dates
         DZA_df = df[df['country']=='DZA']
         DZA_df['datetime'] = pd.to_datetime(DZA_df['date'] + ' ' + DZA_df['time'])
         DZA_df = DZA_df.drop(['date','time'], axis=1)
         DZA_df = DZA_df[['datetime', 'client', 'country', 'ad_type', 'impressions',
                          'value']]
         DZA_df = DZA_df.sort_values(by= ['datetime'])
```

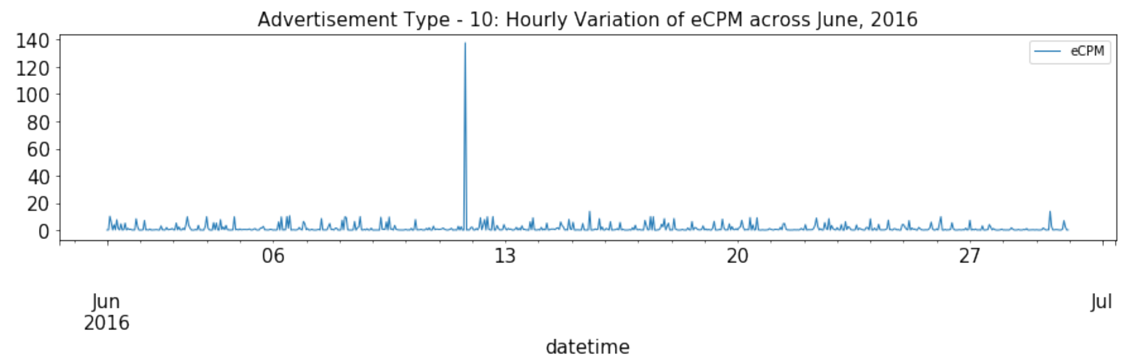
```
DZA_df = DZA_df.dropna()
DZA_df = DZA_df.groupby(['ad_type', 'datetime']).sum()
DZA_df['eCPM'] = ''
DZA_df['eCPM'] = (DZA_df['value']*1000)/(DZA_df['impressions'])
DZA_df = DZA_df.reset_index()
DZA_df.set_index('datetime', inplace=True)
```

In [50]:
```
# dataframes based on ad_types
DZA_02_df = DZA_df[DZA_df['ad_type']== 2]
DZA_10_df = DZA_df[DZA_df['ad_type']==10]
DZA_15_df = DZA_df[DZA_df['ad_type']==15]
DZA_17_df = DZA_df[DZA_df['ad_type']==17]
```

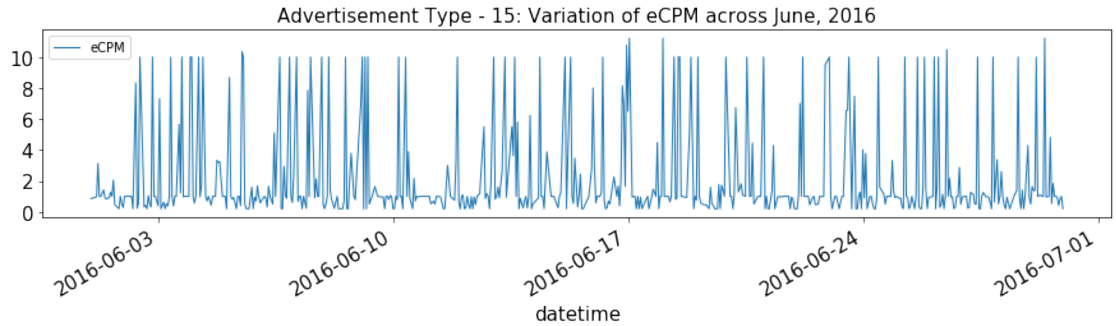
In [51]:
```
DZA_02_df[['eCPM']].plot.line(figsize=(15,3), linewidth=1, fontsize=15)
plt.xlabel('datetime', fontsize=15);
plt.title('Advertisement Type - 2: Hourly Variation of eCPM across June, 2016', fonts
```



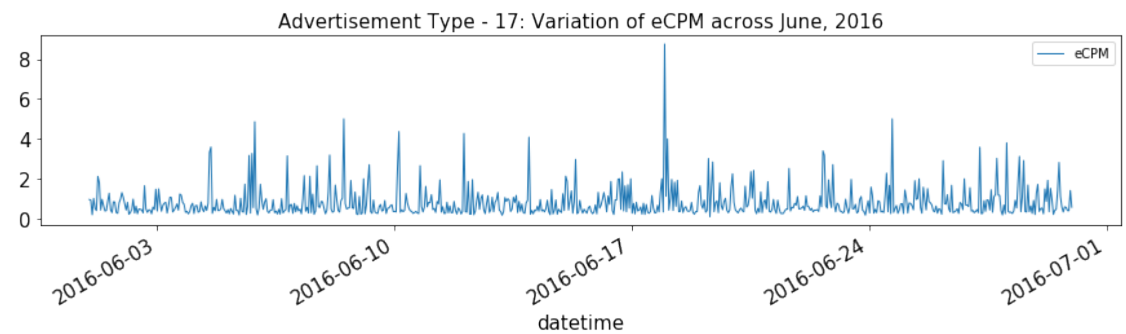
In [43]:
```
DZA_10_df[['eCPM']].plot.line(figsize=(15,3), linewidth=1, fontsize=15)
plt.xlabel('datetime', fontsize=15);
plt.title('Advertisement Type - 10: Hourly Variation of eCPM across June, 2016', fonts
```



```
In [44]: DZA_15_df[['eCPM']].plot.line(figsize=(15,3), linewidth=1, fontsize=15)
         plt.xlabel('datetime', fontsize=15);
         plt.title('Advertisement Type - 15: Variation of eCPM across June, 2016', fontsize=15
```




```
In [45]: DZA_17_df[['eCPM']].plot.line(figsize=(15,3), linewidth=1, fontsize=15)
         plt.xlabel('datetime', fontsize=15);
         plt.title('Advertisement Type - 17: Variation of eCPM across June, 2016', fontsize=15
```



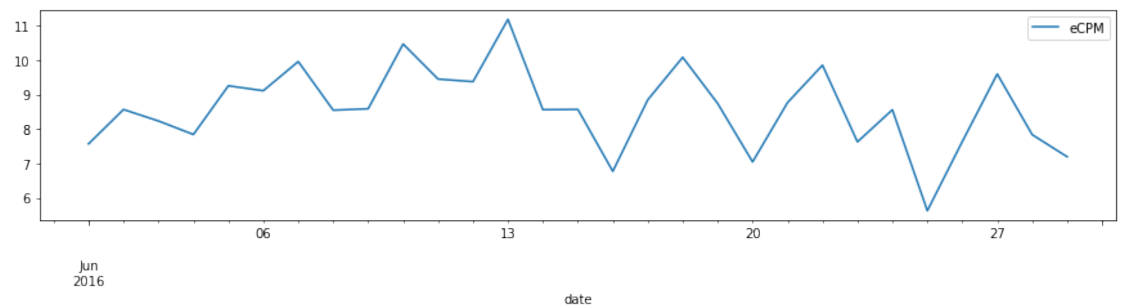
0.5 Forecasting using a Time Series Model

In this segment, we are demonstrating the idea that we can create forecasts for eCPM using the ad_type specific dataframes created for a particular country. In total, we may need 16 time series models to accurately capture the eCPM values for each of the 4 specific ad_type and 4 specific countries. We are demonstrating for NCL with ad_type 2.

```
In [111]: import numpy as np
          from statsmodels.tsa.arima_model import ARIMA
          from statsmodels.graphics.tsaplots import plot_acf
          from statsmodels.graphics.tsaplots import plot_pacf
          from math import sqrt
          from matplotlib import pyplot
```

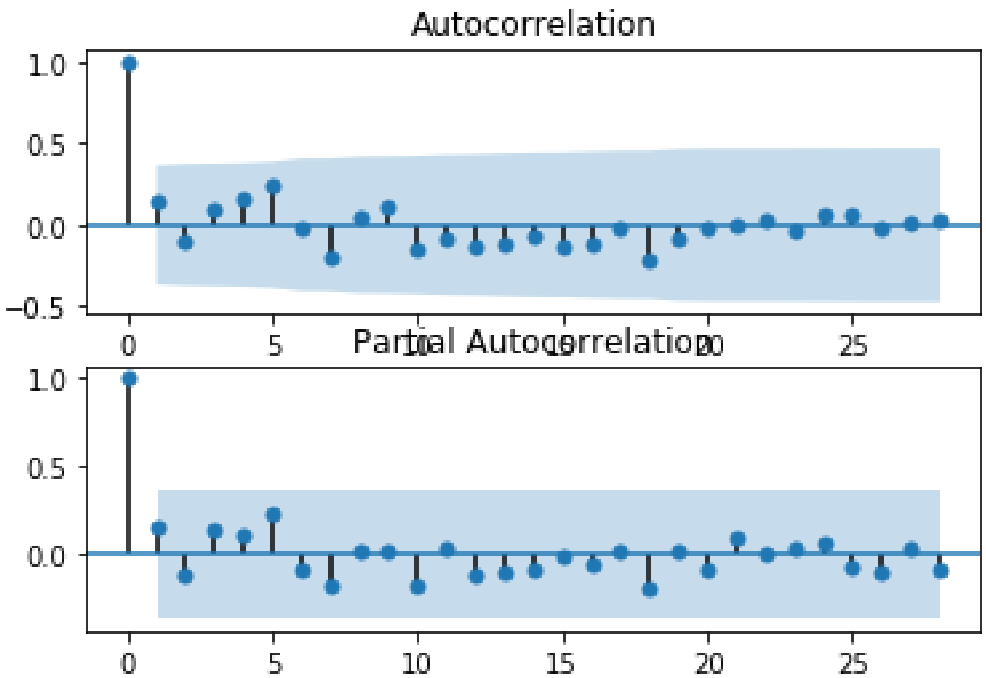
```
In [148]: # visualisation
          series = NCL_02_df[['eCPM']]
          series.plot(figsize=(15,3))
          # univariate series
          print('Variance of original series:',series.var());
          print('Variance of differenced series',series.diff().var());
```

```
('Variance of original series:', eCPM    1.421153
dtype: float64)
('Variance of differenced series', eCPM    2.390404
dtype: float64)
```



As we can clearly see, the series do not have any visible trend. A pattern of seasonality may appear but visibly, it doesn't seem so. Further, the variance of the series also looks pretty fine with little increase as the series progresses. However, at this stage, we will restrict ourselves from taking a logarithmic or square root transformation.

```
In [146]: # examination of acf and pacf
          pyplot.figure()
          pyplot.subplot(211)
          plot_acf(series, ax=pyplot.gca())
          pyplot.subplot(212)
          plot_pacf(series, ax=pyplot.gca())
          pyplot.show()
```



Both ACF and PACF are not showing any significant lags. We may start with p=0, q=0. Although, we may directly plug in these values n an ARIMA model but it would be better if we perform grid search to further develop some idea.

```
In [121]: # Grid search to confirm the chosen model paramters
          # evaluate an ARIMA model for a given order (p,d,q) and return RMSE
          def evaluate_arima_model(X, arima_order):
              # prepare training dataset
              X = X.astype('float32')
              train_size = int(len(X) * 0.50)
              train, test = X[0:train_size], X[train_size:]
              history = [x for x in train]
              # make predictions
              predictions = list()
              for t in range(len(test)):
                  model = ARIMA(history, order=arima_order)
                  # model_fit = model.fit(disp=0)
                  model_fit = model.fit(trend='nc', disp=0)
                  yhat = model_fit.forecast()[0]
                  predictions.append(yhat)
                  history.append(test[t])
              # calculate out of sample error
              mse = mean_squared_error(test, predictions)
              rmse = sqrt(mse)
              return rmse
```

```python
# evaluate combinations of p, d and q values for an ARIMA model
def evaluate_models(dataset, p_values, d_values, q_values):
    dataset = dataset.astype('float32')
    best_score, best_cfg = float("inf"), None
    for p in p_values:
        for d in d_values:
            for q in q_values:
                order = (p,d,q)
                try:
                    mse = evaluate_arima_model(dataset, order)
                    if mse < best_score:
                        best_score, best_cfg = mse, order
                    print('ARIMA%s RMSE=%.3f' % (order,mse))
                except:
                    continue
    print('Best ARIMA%s RMSE=%.3f' % (best_cfg, best_score))


# evaluate parameters
p_values = range(0, 5)
d_values = range(0, 3)
q_values = range(0, 5)
warnings.filterwarnings("ignore")
evaluate_models(series.values, p_values, d_values, q_values)
```

```
ARIMA(0, 0, 1) RMSE=4.836
ARIMA(0, 0, 2) RMSE=4.231
ARIMA(0, 0, 3) RMSE=2.741
ARIMA(0, 1, 1) RMSE=1.469
ARIMA(0, 2, 1) RMSE=1.740
ARIMA(1, 0, 0) RMSE=1.710
ARIMA(1, 1, 0) RMSE=1.737
ARIMA(1, 2, 0) RMSE=2.433
ARIMA(2, 1, 0) RMSE=1.736
ARIMA(2, 2, 0) RMSE=2.421
ARIMA(3, 1, 0) RMSE=1.696
ARIMA(4, 0, 0) RMSE=2.276
ARIMA(4, 1, 0) RMSE=1.634
Best ARIMA(0, 1, 1) RMSE=1.469
```

In [138]:
```python
warnings.filterwarnings('ignore')

# intentionally training on first 25 days and testing on last 15 days due to lack of
train, test = series[['eCPM']].values[0:25], series[['eCPM']].values[15:29]

# fit model
model = ARIMA(train, order=(0,1,1))
```

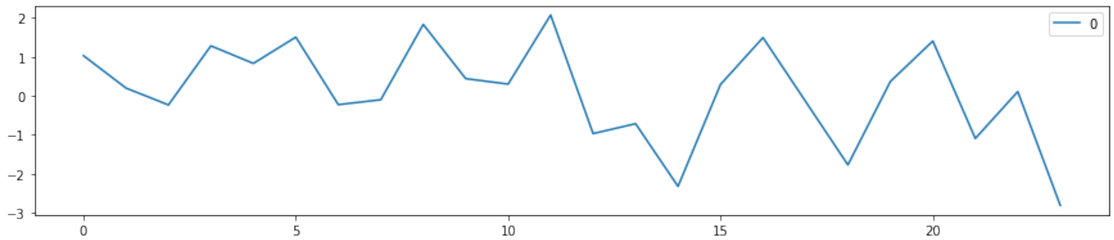
```
model_fit = model.fit(disp=0)
print(model_fit.summary())
```

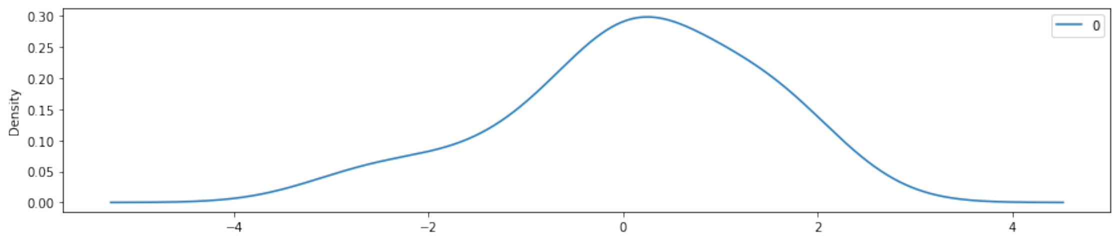
```
                             ARIMA Model Results
==============================================================================
Dep. Variable:                    D.y   No. Observations:                   24
Model:                 ARIMA(0, 1, 1)   Log Likelihood                 -39.667
Method:                       css-mle   S.D. of innovations              1.239
Date:                Sat, 20 Oct 2018   AIC                             85.334
Time:                        14:03:49   BIC                             88.868
Sample:                             1   HQIC                            86.271

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0321      0.066     -0.487      0.631      -0.161       0.097
ma.L1.D.y     -0.7814      0.227     -3.446      0.002      -1.226      -0.337
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
MA.1            1.2797           +0.0000j            1.2797            0.0000
-----------------------------------------------------------------------------
```

In [142]:
```
# plot residual errors

residuals = DataFrame(model_fit.resid)
residuals.plot(figsize=(15,3))
pyplot.show()
residuals.plot(kind='kde', figsize=(15,3))
pyplot.show()
print(residuals.describe())
```






```
               0
count  24.000000
mean    0.114608
std     1.270540
min    -2.817981
25%    -0.355763
50%     0.244304
75%     1.093785
max     2.076164
```

The residuals, although not exactly following normality as we may expect, however, they are somewhat resembling.

```
In [122]: warnings.filterwarnings('ignore')
          from sklearn.metrics import mean_squared_error

          history = [x for x in train]
          predictions = []
          for t in range(len(test)):
              model = ARIMA(history, order=(0,1,1))
              model_fit = model.fit(disp=0)
              output = model_fit.forecast()
              yhat = output[0]
              predictions.extend(yhat)
              obs = test[t]
              history.append(obs)
              print('predicted=%f, expected=%f' % (yhat, obs))
          error = mean_squared_error(test, predictions)
          print('Test MSE: %.3f' % error)
```

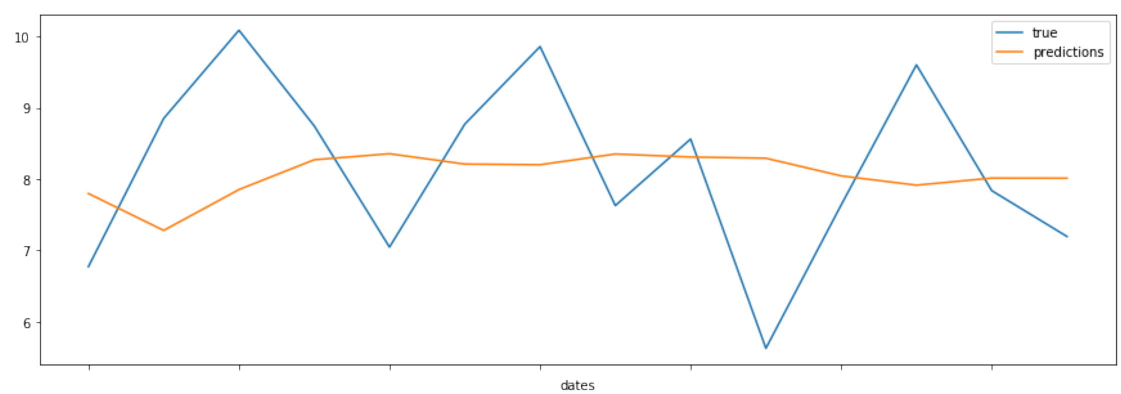
```
predicted=7.798187, expected=6.773410
predicted=7.280596, expected=8.850637
predicted=7.853268, expected=10.087144
predicted=8.271701, expected=8.746229
predicted=8.355729, expected=7.046965
predicted=8.211132, expected=8.770722
predicted=8.201925, expected=9.858574
```

```
predicted=8.352102, expected=7.629319
predicted=8.310149, expected=8.561703
predicted=8.293146, expected=5.628232
predicted=8.045681, expected=7.637763
predicted=7.915104, expected=9.602250
predicted=8.014216, expected=7.838834
predicted=8.012606, expected=7.195957
Test MSE: 1.779
```

```
In [123]: # compute predictions dataframe
          predictions = pd.DataFrame({'predictions':predictions})
          true = [true for true in series['eCPM'][15:29].values]
          predictions['dates'] = date
          predictions['true'] = true
          predictions = predictions[['dates', 'true','predictions']]
          predictions.set_index('dates', inplace=True)
```

```
In [124]: # plot predictions
          predictions.plot(figsize=(15,5))
```

```
Out[124]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa4317515d0>
```



Under this analysis, our idea was to develop one model for each of the advertisement_types for each of the countries as they seems to be following significantly different behaviour from each other as exhibited from their previous plots.

Although, our prediction model seems to be not significantly precise in terms of forecasting the eCPM metric but it hs successfully captured the behaviour in an approximate manner. The values seems to be showing an average of the crests and troughs. A more complex model may be able to capture the specific features but a better remedy would be use several months data and compare the trend and seasonality accordingly. Such metrics often see fluctuations as observed across a year.

LSTM models may also be employed to fit the time series data. However, again, such models need extensively large amount of data.