In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
plt.rcParams['font.sans-serif'] = ['Arial']
plt.rcParams['axes.unicode_minus'] = False
```

In [2]:
```
city = pd.read_excel("city.xlsx")
test = pd.read_excel("test.xlsx")
```

数据概览

In [3]:
```
test.head()
```

Out[3]:

	date	group	requests	gmv	coupon per trip	trips	canceled requests
0	2019-01-01	control	30	7486.620	1.069746	24	1
1	2019-01-02	control	152	38301.575	1.044199	121	8
2	2019-01-03	control	267	67768.425	1.032276	215	14
3	2019-01-04	control	369	94992.900	1.028196	298	19
4	2019-01-05	control	478	123236.875	1.011807	390	24

In [4]:
```
city.head()
```

Out[4]:

	date	hour	requests	trips	supply hours	average minutes of trips	pETA	aETA	utiliz
0	2013-09-01	11	79	55	42.63	20.43	5.51	7.19	0.479240
1	2013-09-01	12	73	41	36.43	15.53	5.48	8.48	0.426297
2	2013-09-01	13	54	50	23.02	17.76	5.07	8.94	0.771503
3	2013-09-02	11	193	170	64.20	31.47	5.31	6.55	0.490187
4	2013-09-02	12	258	210	80.28	38.68	4.94	6.08	0.481814

In [5]:
```
test.describe()
```

Out[5]:

	requests	gmv	coupon per trip	trips	canceled requests
count	58.000000	5.800000e+01	58.000000	58.000000	58.000000
mean	2046.224138	4.820680e+05	0.848199	1633.551724	146.431034
std	1287.778191	2.984599e+05	0.111335	1019.612227	104.260321
min	30.000000	7.382210e+03	0.723737	24.000000	1.000000
25%	968.750000	2.336387e+05	0.756524	799.250000	45.500000
50%	2203.500000	5.092359e+05	0.790527	1745.000000	168.000000
75%	3210.750000	7.495051e+05	0.934330	2553.500000	244.000000
max	4303.000000	1.005137e+06	1.069746	3426.000000	330.000000

In [6]:
```
city.describe()
```

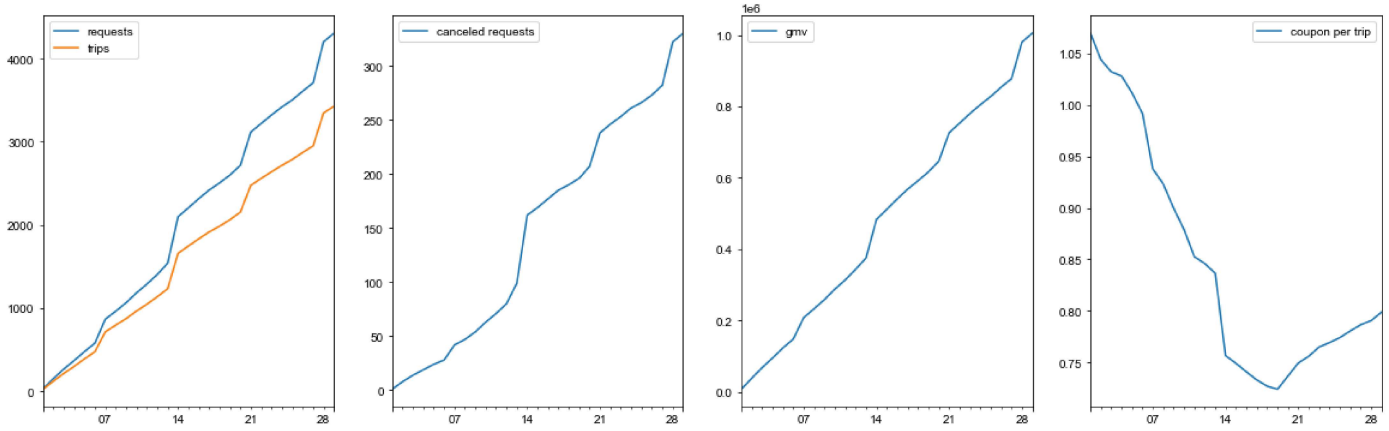
Out[6]:

	hour	requests	trips	supply hours	average minutes of trips	pETA	aETA	utiliz
count	90.000000	90.000000	90.000000	90.000000	90.000000	90.000000	90.00000	90.000000
mean	12.000000	234.411111	149.833333	52.807111	29.051333	5.758556	7.19900	0.558130
std	0.821071	143.187933	105.484889	22.480067	14.343199	1.079037	1.23975	0.159561
min	11.000000	15.000000	6.000000	11.250000	9.050000	2.430000	4.61000	0.299312
25%	11.000000	91.250000	50.000000	32.417500	16.025000	5.085000	6.38250	0.427019
50%	12.000000	234.500000	138.000000	52.570000	27.495000	5.725000	7.06500	0.534818
75%	13.000000	327.750000	238.000000	67.135000	39.055000	6.475000	8.04750	0.669226
max	13.000000	558.000000	420.000000	118.930000	73.620000	8.050000	12.06000	0.970345

数据清洗 数据量虽少，但好在没有缺失值。先将数据拆分为参照组和实验组，这边我用group_A代替参照组，group_B代替实验组。

In [7]:
```
#使用query函数选出对照组设为A,实验组设为B
group_A = test.query('group == "control"')
group_B = test.query('group == "experiment"')
```

In [8]:
```
#创建一个figure画簿,axes轴域,1行,4个,共同使用一个x轴,都为0-28
figure,axes = plt.subplots(1,4,figsize=(20,6),sharex = True)
#生成日期和订单请求数,订单数的线形图
group_A.plot.line(x = 'date', y = ['requests','trips'],ax=axes[0])
group_A.plot.line(x= 'date',y =['canceled requests'] ,ax = axes[1])
group_A.plot.line(x = 'date', y = ['gmv'], ax = axes[2])
group_A.plot.line(x = 'date', y = ['coupon per trip'], ax = axes[3])
for ax in axes:
    ax.set_xlabel("")
    ax.set_xticklabels("")
plt.savefig("./滴滴group_A_original.jpg",dpi=200)
plt.show()
```



In [9]:
```
for col in ['trips','requests','canceled requests','gmv']:
    group_A[f"c_{col}"]=group_A[col].diff().fillna(group_A[col].min())
```

具体查看数据发现,数据集里面储存的为累计数据,需要清洗为每日数据进行查看比较

In [10]:
```
#diff()函数可以计算两行之间的偏差，默认情况下间隔是1行，所以第一行会变为NaN，因此我在后面使用fillna填充第一天的数据
#在订单数,订单请求数,订单取消数,GMV中设置函数
#利用函数,diff()新增几列,diff()函数可以计算两行之间的偏差，默认情况下间隔是1行，所以第一行会变为NaN，因此我在后面使用fillna填充第一天的数据
for col in ['trips','requests','canceled requests','gmv']:
    group_A["c_{col}"]=group_A[col].diff().fillna(group_A[col].min())
```

In [11]:
```
group_A.head()
```

Out[11]:

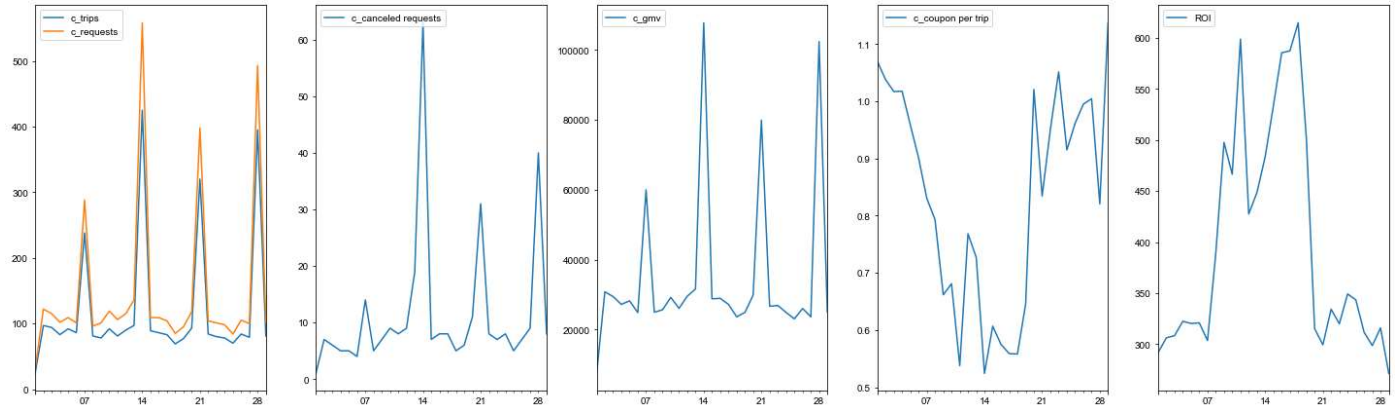
	date	group	requests	gmv	coupon per trip	trips	canceled requests	c_trips	c_requests	c_canceled requests	c_gmv	c_{col}
0	2019-01-01	control	30	7486.620	1.069746	24	1	24.0	30.0	1.0	7486.620	7486.620
1	2019-01-02	control	152	38301.575	1.044199	121	8	97.0	122.0	7.0	30814.955	30814.955
2	2019-01-03	control	267	67768.425	1.032276	215	14	94.0	115.0	6.0	29466.850	29466.850
3	2019-01-04	control	369	94992.900	1.028196	298	19	83.0	102.0	5.0	27224.475	27224.475
4	2019-01-05	control	478	123236.875	1.011807	390	24	92.0	109.0	5.0	28243.975	28243.975

coupon per trip是每单优惠券金额，我猜测的公式应该是：每单优惠券金额=总优惠金额/使用优惠券的订单数，由于数据集的原因呢，实现这个维度的每日拆解我得饶一绕。

先根据原数据集中的coupon per trip和trips相乘，得到累计的优惠券金额coupon_consum 再使用diff计算出每行coupon_consum的偏差，即每天的优惠券使用金额 将每天的优惠券使用金额除以每天的trips得到每天的每单优惠券金额

In [12]:
```
group_A['coupon_consum'] = (group_A['coupon per trip']*group_A['trips'])
group_A['c_coupon'] = group_A['coupon_consum'].diff().fillna(group_A['coupon_consum'].min())
group_A['c_coupon per trip'] = group_A['c_coupon'] / group_A['c_trips']

# 新增ROI，由于缺少具体的盈利数据，所以这边就用每日gmv和每日优惠券金额做个简易的ROI指标
group_A['ROI'] = group_A['c_gmv']/group_A['c_coupon']
```

In [13]:
```
fig, axes = plt.subplots(1, 5, figsize=(20, 6), sharex=True,facecolor='white')
group_A.plot.line(x = 'date',y = ['c_trips','c_requests'],ax=axes[0])
group_A.plot.line(x = 'date',y = ['c_canceled requests'],ax=axes[1])
group_A.plot.line(x = 'date',y = 'c_gmv',ax=axes[2])
group_A.plot.line(x = 'date',y = 'c_coupon per trip',ax=axes[3])
group_A.plot.line(x = 'date',y = 'ROI',ax=axes[4])

for ax in axes:
    ax.set_xlabel("")
    ax.set_xticklabels("")
    ax.legend(loc=2)
plt.tight_layout()
```



这么看起来好像才像正常的运营数据，那把group_B也一并清洗一下。

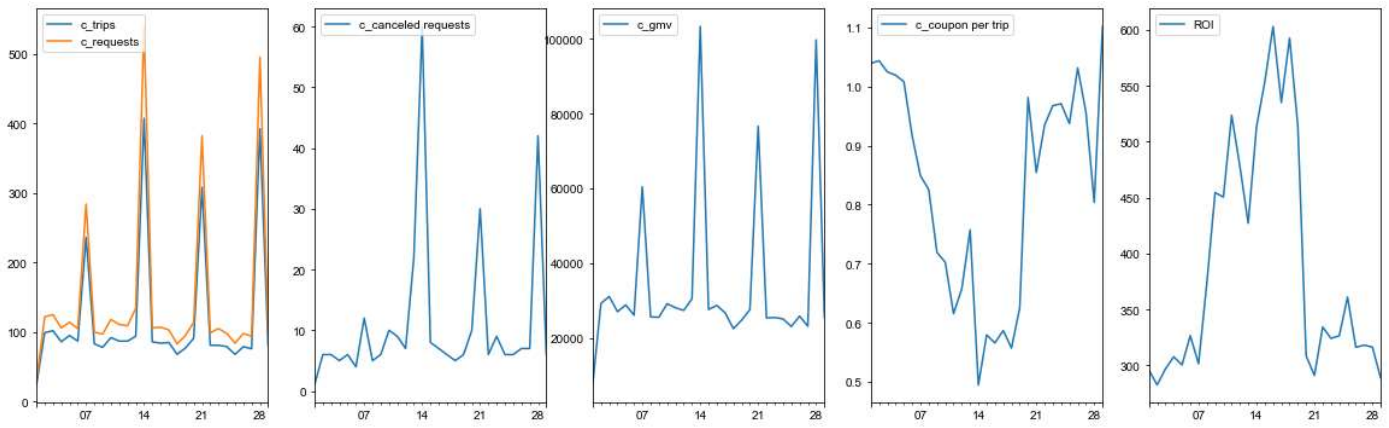
In [14]:
```
group_B.head()
```

Out[14]:

	date	group	requests	gmv	coupon per trip	trips	canceled requests
29	2019-01-01	experiment	30	7382.210	1.039303	24	1
30	2019-01-02	experiment	152	36580.200	1.042920	123	7
31	2019-01-03	experiment	277	67626.375	1.034808	225	13
32	2019-01-04	experiment	383	94601.700	1.030538	311	18
33	2019-01-05	experiment	497	123388.850	1.025366	406	24

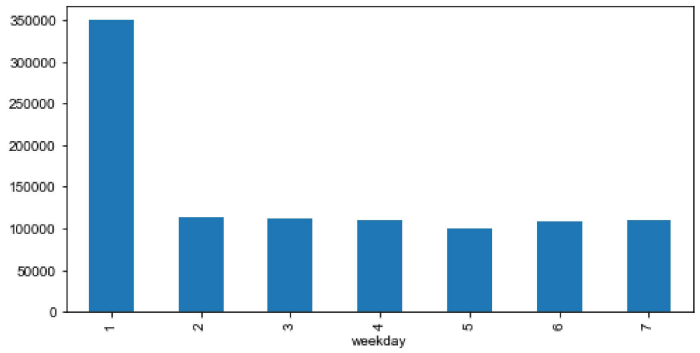
In [15]:
```
for col2 in ['trips','requests','canceled requests','gmv']:
    group_B[f"c_{col2}"]=group_B[col2].diff().fillna(group_B[col2].min())
# 计算每天的每单优惠券金额
group_B ['coupon_consum'] =( group_B['coupon per trip']*group_B['trips'])
group_B ['c_coupon'] = group_B ['coupon_consum'].diff().fillna(group_B ['coupon_consum'].min() )
group_B ['c_coupon per trip'] = group_B ['c_coupon'] / group_B['c_trips']
# 新增ROI，由于缺少具体的盈利数据，所以这边就用每日gmv和每日优惠券金额做个简易的ROI指标
group_B['ROI']= group_B['c_gmv'] / group_B['c_coupon']
```

In [16]:
```
fig,axes = plt.subplots(1,5,figsize= (20,6),sharex = True,facecolor='white')
group_B.plot.line(x = 'date',y = ['c_trips','c_requests'],ax = axes[0])
group_B.plot.line(x = 'date',y = 'c_canceled requests',ax = axes[1])
group_B.plot.line(x = 'date',y = 'c_gmv',ax = axes[2])
group_B.plot.line(x = 'date',y = 'c_coupon per trip',ax = axes[3])
group_B.plot.line(x = 'date',y = 'ROI',ax = axes[4])

for ax2 in axes:
    ax2.set_xlabel("")
    ax2.set_xticklabels("")
    ax2.legend(loc=2)

plt.show()
```



In [17]:
```
group_A ['weekday'] = group_A.date.dt.weekday+1
plt.figure(figsize = (8,4))
group_A.groupby(by = 'weekday').c_gmv.sum().plot.bar()
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x1e5702ed0a0>



In [18]:
```
for i in [group_A,group_B]:
    i['cancel rate']=i['c_canceled requests']/i['c_requests']
    i['accept rate']=i['c_trips']/(i['c_requests']-i['c_canceled requests'])
```

由图可见周一个GMV最高的

AB test效果分析 test总共58条记录，每个组是29条记录，总体标准差未知，使用双样本T检验。\ 零假设：AB两组均值相等\ 备择假设：AB两组均值不等\ 显著性水平：0.05

In [19]:
```
#导入所需要的包
from scipy import stats
ttest = []
for i in ['c_trips', 'c_requests', 'c_canceled requests', 'c_gmv', 'c_coupon per trip', 'ROI', 'accept rate', 'cancel rate']:
    t, p = stats.ttest_rel(group_B[i], group_A[i])
    ttest.append([i, t, p])
pd.DataFrame(ttest, columns=['col', 't', 'p'])
```

Out[19]:

	col	t	p
0	c_trips	-1.302268	0.203436
1	c_requests	-1.471627	0.152273
2	c_canceled requests	-1.262748	0.217095
3	c_gmv	-2.453795	0.020618
4	c_coupon per trip	-0.142977	0.887332
5	ROI	-1.093332	0.283566
6	accept rate	0.402347	0.690484
7	cancel rate	-0.912108	0.369498

可以看出此次ABtest，每日gmv小于0.05，即本次实验前后每日GMV有显著性差异。\ 但每日GMV的T值小于0，即实验组的每日GMV均值小于控制组，由于未知案例中GMV的统计口径，无法对指标拆解，定位背后原因，所以只能笼统地给出方案：“需优化运营策略，再次进行ABtest”。

运营情况分析

In [20]:
```
city.head()
```

Out[20]:

	date	hour	requests	trips	supply hours	average minutes of trips	pETA	aETA	utiliz
0	2013-09-01	11	79	55	42.63	20.43	5.51	7.19	0.479240
1	2013-09-01	12	73	41	36.43	15.53	5.48	8.48	0.426297
2	2013-09-01	13	54	50	23.02	17.76	5.07	8.94	0.771503
3	2013-09-02	11	193	170	64.20	31.47	5.31	6.55	0.490187
4	2013-09-02	12	258	210	80.28	38.68	4.94	6.08	0.481814

根据已给定的维度，我们来考虑一下可以从那几个角度来分析呢：

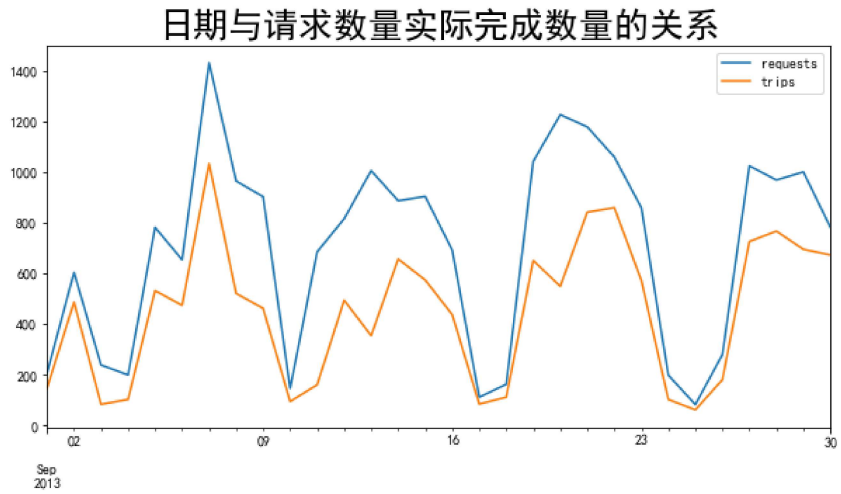
1.时间角度\ 每日、每时段、周内周末指标对比\ 周、月同环比 2.司机角度\ 接单率\ 平均订单时长\ 可服务时长\ 在忙率 3.用户角\ 请求数量\ 取消率\ 等待时长 根据上面几个角度，暂且提出以下问题：

1.给定数据的运营情况走势如何 2.乘客用车高峰期是那个时期，运力能否满足乘客需求 3.顾客预计与等待时间的差异 4.均单时长分布

时间角度 日期与请求数量的关系

In [21]:
```
title_font={'size':25}
label_font={'size':12}
plt.rcParams['font.sans-serif'] = ['SimHei']
city.groupby(by = 'date').agg({
    'requests':'sum',
    'trips':'sum'
}).plot.line(figsize = (10,5))
plt.xlabel(None)
plt.title('日期与请求数量实际完成数量的关系',fontdict=title_font)
```

Out[21]: Text(0.5, 1.0, '日期与请求数量实际完成数量的关系')



由图看出,周末请求数量明显多于工作日,节假日带来更多的出行需求

司机角度 接单率

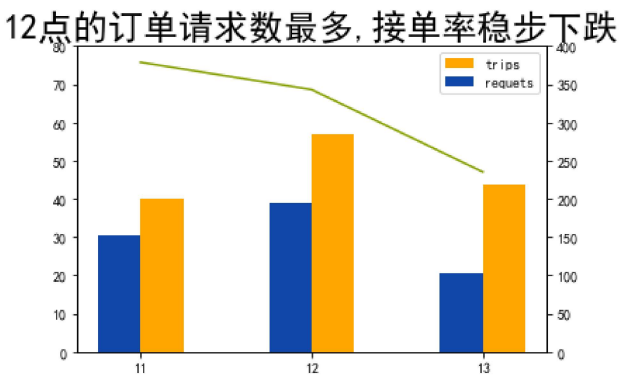
In [22]:
```
accept = city.groupby(by = 'hour') ['requests','trips'].mean()
accept['rate'] = accept['trips']/accept['requests']*100
accept
```

Out[22]:

hour	requests	trips	rate
11	200.266667	151.666667	75.732357
12	284.333333	195.000000	68.581477
13	218.633333	102.833333	47.034609

In [23]:
```
fig,ax1 = plt.subplots()
ax1.plot(accept.index, accept.rate, color='#88a000', label='rate')
ax1.set_ylim(bottom = 0,top = 80)
#产生一个ax1的镜面坐标
ax2 = ax1.twinx()
ax2.bar(accept.index+0.125, accept.requests,width=0.25,color='#ffa500')
ax2.bar(accept.index-0.125, accept.trips,width=0.25,color='#1047a9')
ax2.set_yticks([i for i in range(0, 450, 50)])

plt.xticks([11, 12, 13])
plt.title("12点的订单请求数最多,接单率稳步下跌", fontdict=title_font)
plt.xticks(rotation=0)
plt.legend(['trips', 'requets', 'rate'])
```

Out[23]: <matplotlib.legend.Legend at 0x1e570acf730>



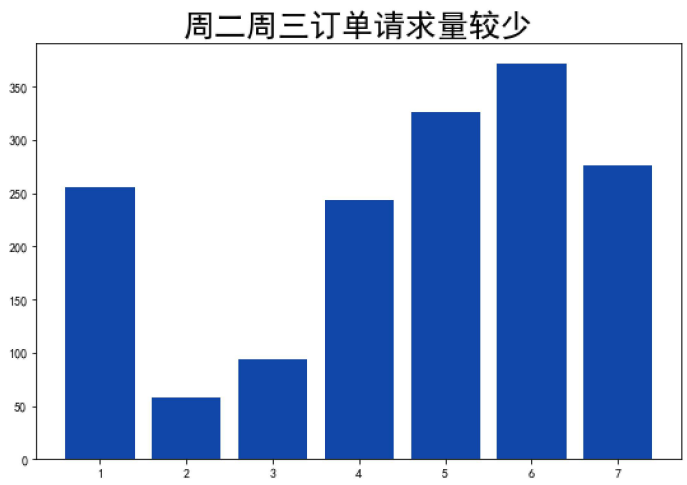
In [28]:
```
#查看当前日期为周几
city ['weekday']= city.date.dt.weekday+1
#新增一列是否为周末,使用匿名函数定义
accept2 = city.groupby(by = ['weekday','hour'])['trips','requests'].mean().apply(lambda x: x.trips/x.requests, axis=1).reset_index().rename({
accept2
```

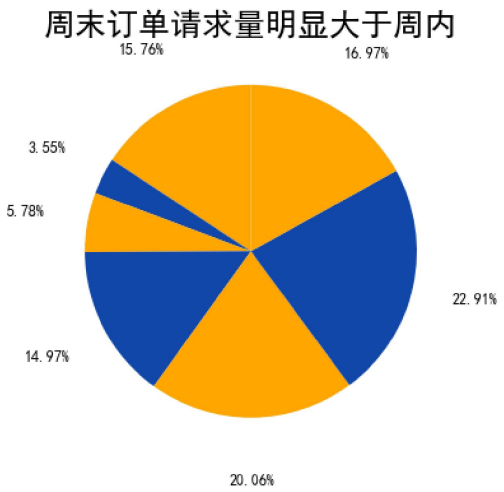
Out[28]:

	weekday	hour	rate
0	1	11	0.811224
1	1	12	0.706405
2	1	13	0.563084
3	2	11	0.548148
4	2	12	0.550781
5	2	13	0.443114
6	3	11	0.400000
7	3	12	0.342939
8	3	13	0.410359
9	4	11	0.712264
10	4	12	0.715278
11	4	13	0.466304
12	5	11	0.819116
13	5	12	0.604353
14	5	13	0.262890
15	6	11	0.833977
16	6	12	0.769352
17	6	13	0.596229
18	7	11	0.821942
19	7	12	0.717904
20	7	13	0.493395

In [57]:
```
fig,axes = plt.subplots(1,2,figsize = (20,6))
#第一个图
ax1 = axes[0]
ax1.bar(x = [i for i in range(1,8)], height=city.groupby(by='weekday').requests.mean(), color='#1047a9', alpha=1)
ax1.set_title("周二周三订单请求量较少", fontdict=title_font)
#第二个图
ax2 = axes[1]
ax2.pie(city.groupby(by='weekday').requests.mean(),autopct="%.2f%%",pctdistance=1.38,startangle=90,colors=['#ffa500', '#1047a9'],textprops=lab
ax2.set_title("周末订单请求量明显大于周内", fontdict=title_font)
```

Out[57]: Text(0.5, 1.0, '周末订单请求量明显大于周内')





周末请求数远高于周内，周六是用车高峰 周二周三的订单请求量最少，其余各天请求量相差不大，周五周六请求量最多 周末的请求量明显大于周内 周末各时段司机接单率都高于周内

等待时长和日期的关系

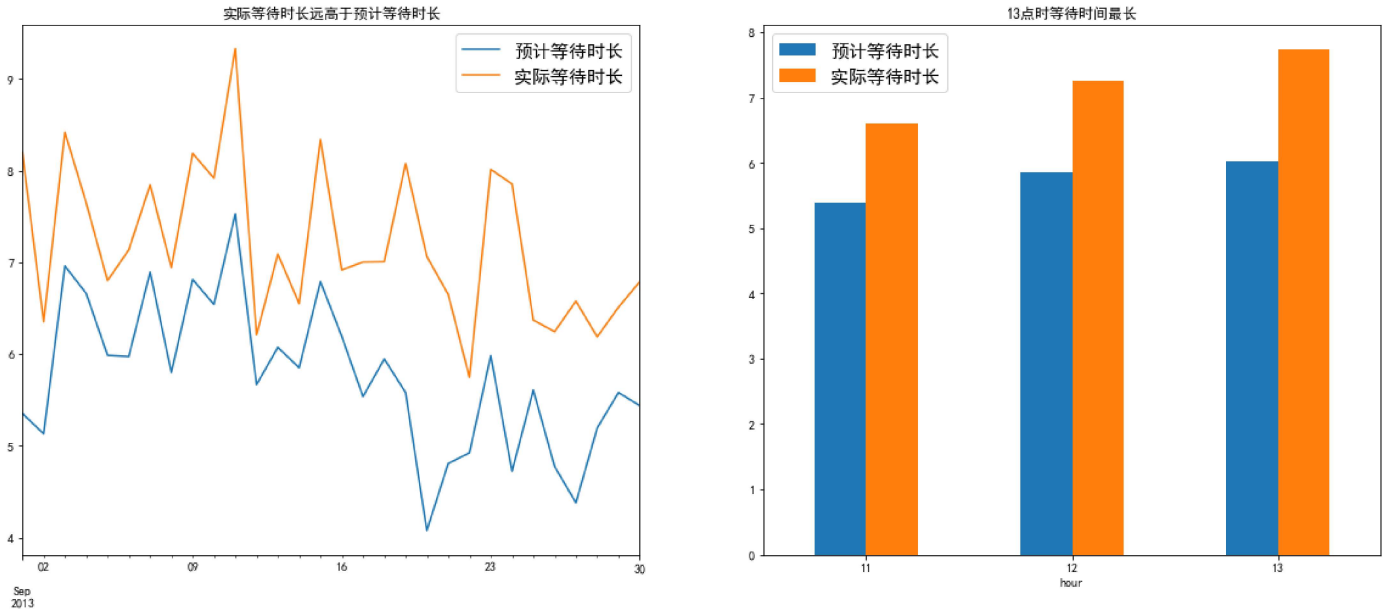
In [58]:
```
city.head()
```

Out[58]:

	date	hour	requests	trips	supply hours	average minutes of trips	pETA	aETA	utiliz	weekday
0	2013-09-01	11	79	55	42.63	20.43	5.51	7.19	0.479240	7
1	2013-09-01	12	73	41	36.43	15.53	5.48	8.48	0.426297	7
2	2013-09-01	13	54	50	23.02	17.76	5.07	8.94	0.771503	7
3	2013-09-02	11	193	170	64.20	31.47	5.31	6.55	0.490187	1
4	2013-09-02	12	258	210	80.28	38.68	4.94	6.08	0.481814	1

In [59]:
```
fig,axes = plt.subplots(1,2,figsize= (20,8))
#第一个图
ax1 = axes[0]
city.groupby('date')['pETA','aETA'].mean().plot.line(ax=ax1)
ax1.set_title('实际等待时长远高于预计等待时长')
ax1.set_xlabel(None)
ax1.legend(['预计等待时长', '实际等待时长'],fontsize= 15)

#第二个图
ax2 = axes[1]
city.groupby('hour')['pETA','aETA'].mean().plot.bar(ax=ax2)
ax2.set_title('13点时等待时间最长')
ax2.set_xticklabels([11, 12, 13], rotation=0)
ax2.legend(['预计等待时长','实际等待时长'],fontsize= 15)
```

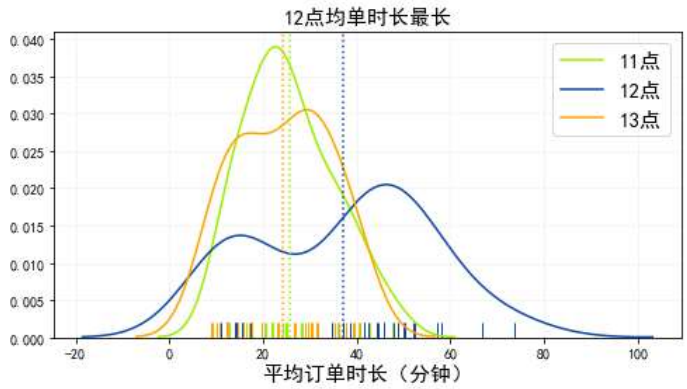
Out[59]: <matplotlib.legend.Legend at 0x1e5702684f0>



实际等待时长远高于预计等待时长 1.统计时段内顾客实际等待时长逐渐减少，可能是配送车辆增加，优化了路线 2.11-13点这段时间内实际等待时长逐渐增加，13点的实际等待时长最久 3.预计等待时长与实际等待时长相差过大，仍需要迭代更新时间预估模块，优化派单逻辑 4.实际等待时间长可能是司机都在忙，运力不足

In [61]:
```
plt.figure(figsize=(8, 4), facecolor='white')
sns.distplot(city[city.hour == 11]['average minutes of trips'], color='#9fee00',hist=False,kde=True,rug = True,label = '11点')
sns.distplot(city[city.hour == 12]['average minutes of trips'], color='#1047a9',hist=False,kde=True,rug = True,label = '12点')
sns.distplot(city[city.hour == 13]['average minutes of trips'], color='#ffa500',hist=False,kde=True,rug = True,label = '13点')

plt.axvline(city[city.hour == 11]['average minutes of trips'].mean(),color='#9fee00', linestyle=":")
plt.axvline(city[city.hour == 12]['average minutes of trips'].mean(), color='#1047a9', linestyle=":" )
plt.axvline(city[city.hour == 13]['average minutes of trips'].mean(), color='#ffa500',  linestyle=":")

plt.grid(linestyle="--", alpha=0.2)
plt.title("12点均单时长最长",fontsize= 15)
plt.xlabel("平均订单时长（分钟）",fontsize= 15)
plt.legend(['11点','12点','13点'],fontsize= 15)
```

Out[61]: <matplotlib.legend.Legend at 0x1e5706e7910>

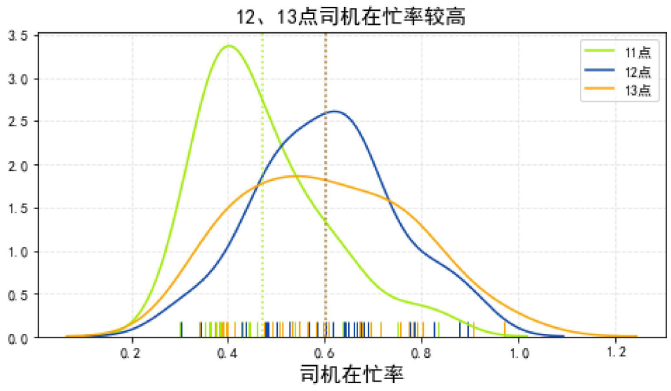


11、13点这两个时段的均单时长较短，12点的均单时长最长

In [62]:

```
plt.figure(figsize = (8,4))
sns.distplot(city[city.hour == 11]["utiliz"], color='#9fee00',hist=False,kde=True,rug = True,label = '11点')
sns.distplot (city[city.hour==12]['utiliz'],color='#1047a9',hist=False,kde=True,rug = True,label = '12点')
sns.distplot(city[city.hour==13]['utiliz'],color='#ffa500' ,hist=False,kde=True,rug = True,label = '13点')
#加入平均线
plt.axvline(city[city.hour == 11]['utiliz'].mean(), color='#9fee00', linestyle=":", alpha=0.8)
plt.axvline(city[city.hour == 12]['utiliz'].mean(), color='#1047a9', linestyle=":", alpha=0.8)
plt.axvline(city[city.hour == 13]['utiliz'].mean(), color='#ffa500', linestyle=":", alpha=0.8)
#设置背景为格,透明度0.3
plt.grid(linestyle="--", alpha=0.3)
plt.xlabel('司机在忙率',fontsize = 15)
plt.title("12、13点司机在忙率较高",fontsize = 15)
```

Out[62]: Text(0.5, 1.0, '12、13点司机在忙率较高')



可以认为是12、13点司机在忙率较高，所以导致了12、13点的接单率下降，顾客实际等待时间增加。

相关性检测

In [64]:

```
city['rate']=city.trips/city.requests
city.corr().style.background_gradient('OrRd')
```

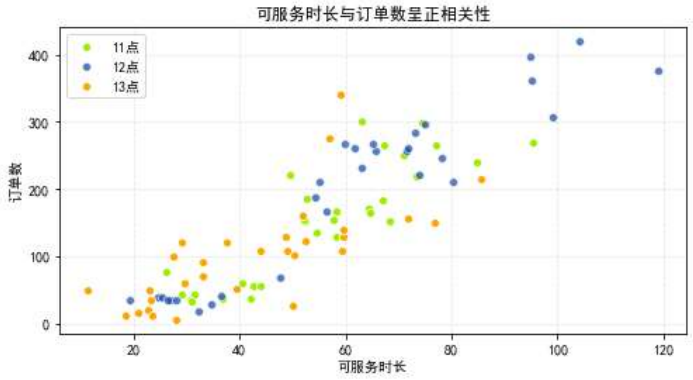
Out[64]:

	hour	requests	trips	supply hours	average minutes of trips	pETA	aETA	utiliz	weekday	rate
hour	1.000000	0.052659	-0.190054	-0.234614	-0.035950	0.236269	0.371433	0.334071	0.000000	-0.468675
requests	0.052659	1.000000	0.837015	0.654692	0.810837	-0.007639	0.025894	0.413997	0.420478	-0.041166
trips	-0.190054	0.837015	1.000000	0.880738	0.907870	-0.151332	-0.259215	0.198133	0.408854	0.435483
supply hours	-0.234614	0.654692	0.880738	1.000000	0.827092	-0.312910	-0.487399	-0.118937	0.421520	0.535273
average minutes of trips	-0.035950	0.810837	0.907870	0.827092	1.000000	0.021548	-0.058355	0.412460	0.386764	0.287043
pETA	0.236269	-0.007639	-0.151332	-0.312910	0.021548	1.000000	0.634522	0.560360	-0.158184	-0.354286
aETA	0.371433	0.025894	-0.259215	-0.487399	-0.058355	0.634522	1.000000	0.665902	-0.155170	-0.565313
utiliz	0.334071	0.413997	0.198133	-0.118937	0.412460	0.560360	0.665902	1.000000	0.061231	-0.399438
weekday	0.000000	0.420478	0.408854	0.421520	0.386764	-0.158184	-0.155170	0.061231	1.000000	0.105339
rate	-0.468675	-0.041166	0.435483	0.535273	0.287043	-0.354286	-0.565313	-0.399438	0.105339	1.000000

从上图可以看出trips和supply hours有较强的相关性，接单率与supply hours仅有较弱的相关性

In [65]:

```
plt.figure(figsize=(8, 4), facecolor='white')

sns.scatterplot(x='supply hours', y='trips',data=city[city.hour == 11], label='11点', color='#9fee00',alpha=1)
sns.scatterplot(x='supply hours', y='trips',data=city[city.hour == 12], label='12点', color='#1047a9',alpha=0.7)
sns.scatterplot(x='supply hours', y='trips',data=city[city.hour == 13], label='13点', color='#ffa500',alpha=1)

plt.grid(linestyle="--", alpha=0.3)
plt.title("可服务时长与订单数呈正相关性")
plt.xlabel("可服务时长")
plt.ylabel("订单数")
plt.show()
```



总结 时间维度 1.统计周期内的运营情况呈现周期性波动，周末的订单请求数较多，周二周三的订单量较少，中午12点的请求量最多 2.周末各时段接单率都高于周内，但仍随着时间推移接单率下降 司机维度 1.预计等待时长与实际等待时长存在一定差异，实际等待时长随着时间推移而增加，13点的实际等待时长最久 2.12点均单时长最长，接单率下降幅度较少，11点的均单时长稍长于13点，但接单率远高于13点。 3.司机在忙率的提高导致接单率下降，顾客等待时长增加。 建议 1.提高运力，增加司机及配车，减少高峰时段的运营压力 2.优化时间预计算法，提高用户体验，优化订单分配及路线规划算法，提高司机的抢单及接送速度 3.适当发放限时优惠券，限定在12点之前使用，减少12、13点的接单压力 4.适当增加12、13点时间段内对于司机的补贴，加快接单速度，提高运营效率