ATE estimations from real observational data

This notebook examines the use of Bayesian Networks for estimating Average Treatment Effects (ATE) in Observational Studies within the Neyman-Rubin potential outcome framework from real data: N. Antonio et al. (2019)

In [2]:

```python
import pyAgrum as gum
import pyAgrum.lib.notebook as gnb
import pyAgrum.skbn as skbn
import pyAgrum.causal as csl
import pyAgrum.causal.notebook as cslnb

import numpy as np
import pandas as pd

import matplotlib.pyplot as plt

pd.set_option('future.no_silent_downcasting', True)
```

Dataset

The data used in this notbook come from "Hotel booking demand datasets" by N. Antonio et al. The data contains 31 variables describing the 104,641 observations. Each observation represents a hotel booking.

We aim to study the impact of assigning a different room to a customer on its likelihood to cancel the reservation. Here, some data preprocessing is needed to match our objectives.

In [3]:

```python
df = pd.read_csv("../data/hotel_bookings.csv")
df.head()
```

Out[3]:

	hotel	is_canceled	lead_time	arrival_date_year	arrival_date_month	arrival_date_week_number	arrival_date_day_of_month	stays_in_weekend_nights	stays_in_week_nights	adults	...	deposit_type	agent
0	Resort Hotel	0	342	2015	July	27	1	0	0	2	...	No Deposit	NaN
1	Resort Hotel	0	737	2015	July	27	1	0	0	2	...	No Deposit	NaN
2	Resort Hotel	0	7	2015	July	27	1	0	1	1	...	No Deposit	NaN
3	Resort Hotel	0	13	2015	July	27	1	0	1	1	...	No Deposit	304.0
4	Resort Hotel	0	14	2015	July	27	1	0	2	2	...	No Deposit	240.0

5 rows × 32 columns

In [4]:

```python
# Total stay in nights
df['total_stay'] = df['stays_in_week_nights'] + df['stays_in_weekend_nights']

# Total number of guests
df['guests'] = df['adults'] + df['children'] + df['babies']

# Creating the different_room_assigned feature
df['different_room_assigned'] = 0
slice_indices = df['reserved_room_type'] != df['assigned_room_type']
df.loc[slice_indices,'different_room_assigned'] = 1

# Deleting older features
df = df.drop(['stays_in_week_nights','stays_in_weekend_nights','adults','children',
                   'babies','reserved_room_type','assigned_room_type'],axis=1)

df.columns
```

Out[4]:

```
Index(['hotel', 'is_canceled', 'lead_time', 'arrival_date_year',
       'arrival_date_month', 'arrival_date_week_number',
       'arrival_date_day_of_month', 'meal', 'country', 'market_segment',
       'distribution_channel', 'is_repeated_guest', 'previous_cancellations',
       'previous_bookings_not_canceled', 'booking_changes', 'deposit_type',
       'agent', 'company', 'days_in_waiting_list', 'customer_type', 'adr',
       'required_car_parking_spaces', 'total_of_special_requests',
       'reservation_status', 'reservation_status_date', 'total_stay', 'guests',
       'different_room_assigned'],
      dtype='object')
```

In [5]:

```python
print(f"Number of Null entries: {df.isnull().sum()}")
df = df.drop(['agent','company'],axis=1)

# Replacing missing countries with most freqently occuring countries
df['country']= df['country'].fillna(df['country'].mode()[0])
df['guests']= df['guests'].fillna(df['guests'].mode()[0]).astype(int)

df = df.drop(['reservation_status','reservation_status_date','arrival_date_day_of_month'],axis=1)
df = df.drop(['arrival_date_year'],axis=1)
df = df.drop(['distribution_channel'], axis=1)
```

```
Number of Null entries: hotel                                 0
is_canceled                         0
lead_time                           0
arrival_date_year                   0
arrival_date_month                  0
arrival_date_week_number            0
arrival_date_day_of_month           0
meal                                0
country                           488
market_segment                      0
distribution_channel                0
is_repeated_guest                   0
previous_cancellations              0
previous_bookings_not_canceled      0
booking_changes                     0
deposit_type                        0
agent                           16340
company                        112593
days_in_waiting_list                0
customer_type                       0
adr                                 0
required_car_parking_spaces         0
total_of_special_requests           0
reservation_status                  0
reservation_status_date             0
total_stay                          0
guests                              4
different_room_assigned             0
dtype: int64
```

In [6]:

```python
# Replacing 1 by True and 0 by False for the experiment and outcome variables
df['different_room_assigned']= df['different_room_assigned'].replace(1,True)
df['different_room_assigned']= df['different_room_assigned'].replace(0,False)
df['is_canceled']= df['is_canceled'].replace(1,True)
df['is_canceled']= df['is_canceled'].replace(0,False)
```

```
df.dropna(inplace=True)
print(df.columns)
df.iloc[:, 5:20].head()
```

```
Index(['hotel', 'is_canceled', 'lead_time', 'arrival_date_month',
       'arrival_date_week_number', 'meal', 'country', 'market_segment',
       'is_repeated_guest', 'previous_cancellations',
       'previous_bookings_not_canceled', 'booking_changes', 'deposit_type',
       'days_in_waiting_list', 'customer_type', 'adr',
       'required_car_parking_spaces', 'total_of_special_requests',
       'total_stay', 'guests', 'different_room_assigned'],
      dtype='object')
```

Out[6]:

	meal	country	market_segment	is_repeated_guest	previous_cancellations	previous_bookings_not_canceled	booking_changes	deposit_type	days_in_waiting_list	customer_type	adr	required_car_parking_s
0	BB	PRT	Direct	0	0	0	3	No Deposit	0	Transient	0.0	
1	BB	PRT	Direct	0	0	0	4	No Deposit	0	Transient	0.0	
2	BB	GBR	Direct	0	0	0	0	No Deposit	0	Transient	75.0	
3	BB	GBR	Corporate	0	0	0	0	No Deposit	0	Transient	75.0	
4	BB	GBR	Online TA	0	0	0	0	No Deposit	0	Transient	98.0	

In [7]:
```
df = df[df.deposit_type=="No Deposit"]
df.groupby(['deposit_type','is_canceled']).count()
```

Out[7]:

		hotel	lead_time	arrival_date_month	arrival_date_week_number	meal	country	market_segment	is_repeated_guest	previous_cancellations	previous_bookings_not_canceled	booki
deposit_type	**is_canceled**											
No Deposit	**False**	74947	74947	74947	74947	74947	74947	74947	74947	74947	74947	
	True	29694	29694	29694	29694	29694	29694	29694	29694	29694	29694	

In [8]:
```
counts_sum=0
for i in range(1,1000):
        counts_i = 0
        rdf = df.sample(1000)
        counts_i = rdf[rdf["is_canceled"] == rdf["different_room_assigned"]].shape[0]
        counts_sum+= counts_i
print(f"Percentage of customers with different room assignment and cancelation : {counts_sum/1000000}")
```

```
Percentage of customers with different room assignment and cancelation : 0.588294
```

In [9]:
```
# Expected Count when there are no booking changes
counts_sum=0
for i in range(1,1000):
        counts_i = 0
        rdf = df[df["booking_changes"]==0].sample(1000)
        counts_i = rdf[rdf["is_canceled"] == rdf["different_room_assigned"]].shape[0]
        counts_sum+= counts_i
counts_sum/1000000
print(f"Percentage of customers with different room assignment and cancelation when there are no booking changes : {counts_sum/1000000}")
```

```
Percentage of customers with different room assignment and cancelation when there are no booking changes : 0.572001
```

In [10]:
```
# Expected Count when there are booking changes = 66.4%
counts_sum=0
for i in range(1,1000):
        counts_i = 0
        rdf = df[df["booking_changes"]>0].sample(1000)
        counts_i = rdf[rdf["is_canceled"]== rdf["different_room_assigned"]].shape[0]
        counts_sum+= counts_i
counts_sum/1000000
print(f"Percentage of customers with different room assignment and cancelation when there are booking changes : {counts_sum/1000000}")
```

```
Percentage of customers with different room assignment and cancelation when there are booking changes : 0.665402
```

In [11]:
```
df = df.drop(columns=["customer_type", "arrival_date_month", "arrival_date_week_number", "adr", "previous_cancellations", "deposit_type"])
```

We observe that changes in a customer's booking may influence the probability of different room assignments and booking cancellations. We will now investigate whether a causal relationship exists between these factors.

Bayesian Network Preparation

We use `skbn.BNDiscretizer` to discretize the continous variables found in the dataset. The structure of the network will also be provided, `gum.BNLearner` will be used for parameter learning.

In [12]:
```
for var in df.select_dtypes(include='number').columns:
    print(var, df[var].nunique())
```

```
lead_time 431
is_repeated_guest 2
previous_bookings_not_canceled 73
booking_changes 21
days_in_waiting_list 99
required_car_parking_spaces 5
total_of_special_requests 6
total_stay 45
guests 15
```

In [13]:
```
disc = skbn.BNDiscretizer(defaultNumberOfBins=5, defaultDiscretizationMethod="kmeans") #uniform causes the kernel to crash

disc.setDiscretizationParameters(variableName="lead_time", method="quantile")
disc.setDiscretizationParameters(variableName="is_repeated_guest", method="NoDiscretization")
disc.setDiscretizationParameters(variableName="previous_bookings_not_canceled", method="kmeans")
disc.setDiscretizationParameters(variableName="booking_changes", method="kmeans", paramDiscretizationMethod=5)
disc.setDiscretizationParameters(variableName="days_in_waiting_list", method="kmeans", paramDiscretizationMethod=5)
disc.setDiscretizationParameters(variableName="guests", method="kmeans", paramDiscretizationMethod=5)
disc.setDiscretizationParameters(variableName="total_stay", method="quantile")

template = disc.discretizedBN(df)
```

```
/home/thierry/.local/lib/python3.10/site-packages/sklearn/preprocessing/_discretization.py:307: UserWarning: Bins whose width are too small (i.e., <= 1e-8) in feature 0 are removed. Consi
der decreasing the number of bins.
  warnings.warn(
```

In [14]:
```
template.addArc("market_segment", "lead_time")
template.addArc("lead_time", "is_canceled")
template.addArc("country", "lead_time")
template.addArc("different_room_assigned", "is_canceled")
template.addArc("country", "meal")
template.addArc("lead_time", "days_in_waiting_list")
template.addArc("days_in_waiting_list", "is_canceled")
template.addArc("days_in_waiting_list", "different_room_assigned")
template.addArc("previous_bookings_not_canceled", "is_canceled")
template.addArc("previous_bookings_not_canceled", "is_repeated_guest")
template.addArc("is_repeated_guest", "different_room_assigned")
template.addArc("is_repeated_guest", "is_canceled")
template.addArc("total_stay", "is_canceled")
template.addArc("guests", "is_canceled")
template.addArc("booking_changes", "different_room_assigned")
template.addArc("booking_changes", "is_canceled")
template.addArc("hotel", "different_room_assigned")
template.addArc("hotel", "is_canceled")
template.addArc("required_car_parking_spaces", "is_canceled")
template.addArc("total_of_special_requests", "booking_changes")
template.addArc("total_of_special_requests", "is_canceled")
template.addArc("country", "hotel")
template.addArc("country", "required_car_parking_spaces")
template.addArc("country", "total_of_special_requests")
template.addArc("market_segment", "hotel")
template.addArc("market_segment", "required_car_parking_spaces")
template.addArc("market_segment", "total_of_special_requests")
```

In [15]:

```
learner = gum.BNLearner(df, template)
learner.useNMLCorrection()
learner.useSmoothingPrior(1e-9)

bn = gum.BayesNet(template)
learner.fitParameters(bn)
```

Out[15]:

```
(pyAgrum.BNLearner<double>@0x609ec7fc08e0) Filename       : /tmp/tmp8v165az6.csv
Size           : (104641,15)
Variables      : hotel[2], is_canceled[2], lead_time[5], meal[5], country[177], market_segment[8], is_repeated_guest[2], previous_bookings_not_canceled[5], booking_changes[5], days_in_w
aiting_list[5], required_car_parking_spaces[5], total_of_special_requests[6], total_stay[4], guests[5], different_room_assigned[2]
Induced types  : False
Missing values : False
Algorithm      : MIIC
Score          : BDeu  (Not used for constraint-based algorithms)
Correction     : NML  (Not used for score-based algorithms)
Prior          : Smoothing
Prior weight   : 0.000000
```

Causal Model

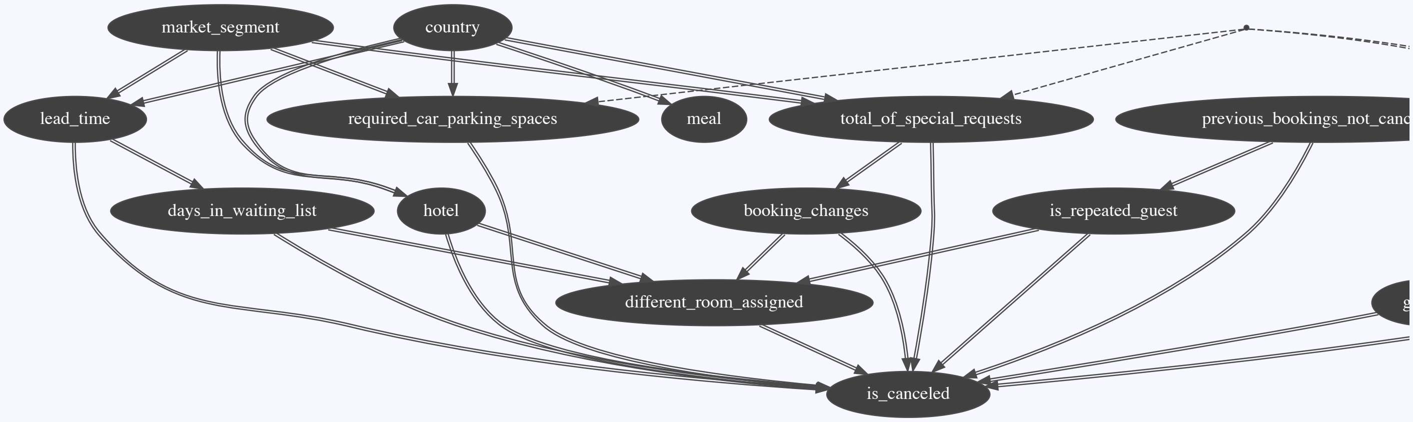
A causal Baysian Network is then created using `csl.CausalModel`, a latent variable being the cause of multiple covariates is also added.

In [16]:

```
cslbn = csl.CausalModel(bn, [("U", ["total_of_special_requests", "required_car_parking_spaces", "total_stay", "guests"])])
```

In [17]:

```
cslnb.showCausalModel(cslbn, size="50")
```



In [18]:

```
T = "different_room_assigned"
Y = "is_canceled"
```

In [19]:

```
cslnb.showCausalImpact(cslbn, doing=T, on=Y, values={T:1})
```

Causal Model

$$P(is_canceled \mid \text{do}(different_room_assigned)) =$$

$$\sum_{booking_changes,days_in_waiting_list,hotel,is_repeated_guest} P\left(is_canceled \mid booking_changes, days_in_waiting_list, different_room_assigned, hotel, is_repeated_guest\right) \cdot P\left(booking_changes, days_in_waiting_list, hotel, is_repeated_guest\right)$$

Explanation : backdoor ['hotel', 'is_repeated_guest', 'booking_changes', 'days_in_waiting_list'] found.

is_canceled	
False	True
0.9224	0.0776

Impact

In [20]:

```
cslnb.showCausalImpact(cslbn, doing=T, on=Y, values={T:0})
```

Causal Model

$$P(is_canceled \mid \mathrm{do}(different_room_assigned)) = \sum_{booking_changes, days_in_waiting_list, hotel, is_repeated_guest} P\left(is_canceled \mid booking_changes, days_in_waiting_list, different_room_assigned, hotel, is_repeated_guest\right) \cdot P\left(booking_changes, days_in_waiting_list, hotel, is_repeated_guest\right)$$

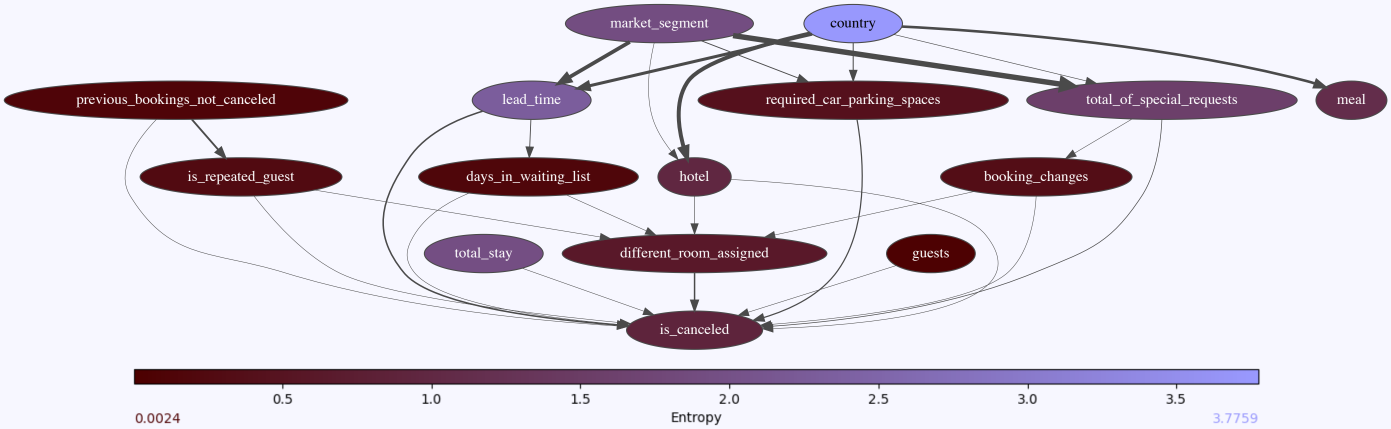
Explanation : backdoor ['hotel', 'is_repeated_guest', 'booking_changes', 'days_in_waiting_list'] found.

is_canceled	
False	**True**
0.6693	0.3307

Impact

```
In [21]: gnb.showInformation(bn, size="50")
```

```
[pyAgrum] pyAgrum.lib.notebook.showInformation is deprecated since 0.20.2. Please use pyAgrum.lib.explain.showInfomation instead.
```



```
In [22]: _, cpt0, _ = csl.causalImpact(cslbn, on=Y, doing=T, values={T:0})
         _, cpt1, _ = csl.causalImpact(cslbn, on=Y, doing=T, values={T:1})
         diff = cpt1 - cpt0
         ate = diff.expectedValue(lambda d : diff.variable(0).numerical(d[diff.variable(0).name()]))
         print(f"{ate = }")
```

```
ate = -0.2531058345752799
```

We observe a negative Average Treatment Effect (ATE), which is counterintuitive, as it suggests that assigning a different room reduces the likelihood of a reservation cancellation. To explore this further, we will examine the Conditional Average Treatment Effect (CATE) by conditioning on the covariates to provide additional insights.

CATE estimations

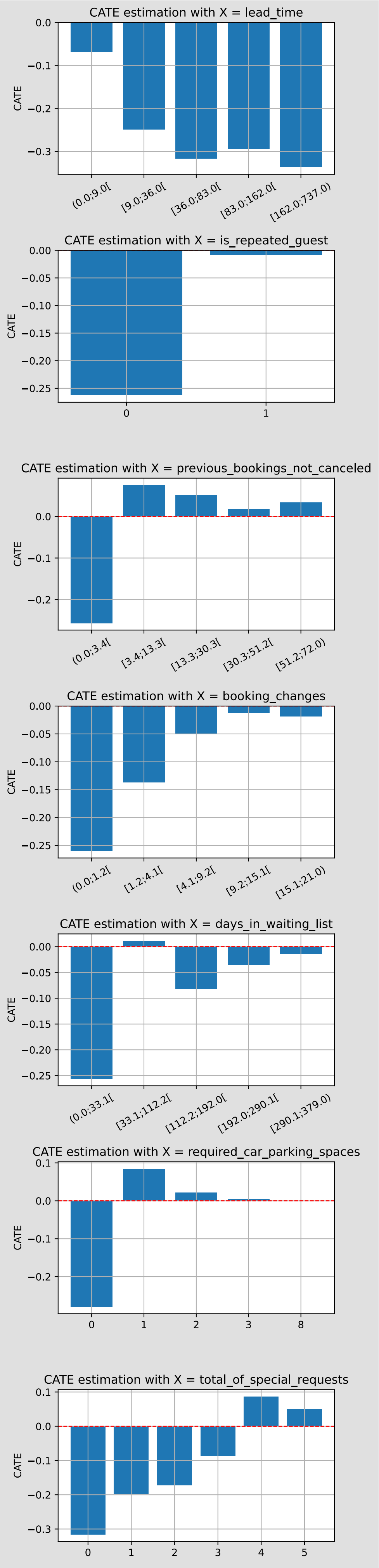
```
In [23]: def mutilateBN(bn : gum.BayesNet) -> gum.BayesNet:
             """
             Returns a copy of the Bayesian Network with all incoming arcs to the variable T removed.
             """
             res = gum.BayesNet(bn)
             for p_id in bn.parents(T):
                 res.eraseArc(p_id, bn.idFromName(T))
             return res

         def ATE(bn, X = {}, mutilate = True):
             """
             """

             ie = gum.LazyPropagation(mutilateBN(bn)) if mutilate else gum.LazyPropagation(bn)

             ie.setEvidence({T: 0} | X)
             ie.makeInference()
             p0 = ie.posterior(Y)

             ie.chgEvidence(T,1)
             ie.makeInference()
             p1 = ie.posterior(Y)

             diff = p1 - p0
             return diff.expectedValue(lambda d : diff.variable(0).numerical(d[diff.variable(0).name()]))

         def cond_ATE_evo(bn, target):
             """
             """
             ate_list = list()
             for i in range(bn.variable(target).domainSize()):
                 ate_list.append(ATE(bn, {target:i}))
             return ate_list
```

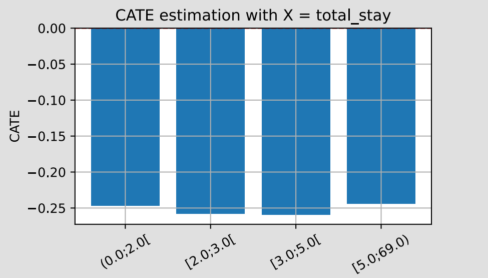
```
In [24]: def get_xticks(var):
             var_type = var.varType()

             if var_type == 0:
                 domain = var.domain()[1:-1].split(",")
                 domain = [interval[1:-1].split(";") for interval in domain]
                 domain = [f"[{float(interval[0]):.1f};{float(interval[1]):.1f}[" for interval in domain]
                 domain[0] = "(" + domain[0][1:]
                 domain[-1] = domain[-1][:-1] + ")"
             elif var_type == 2:
                 domain = var.domain()[1:-1].split("|")
             elif var_type == 4:
                 start_end = var.domain()[1:-1].split(",")
                 domain = [str(i) for i in range(int(start_end[0]), int(start_end[1])+1)]
             else:
```

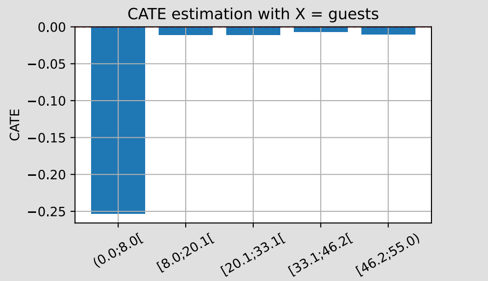
```
        domain = var.domain()
    return domain
```

In [32]:

```
covar_list = df.select_dtypes(include='number').columns

plt.subplots(figsize=(5,4*len(covar_list)))

for i in range(len(covar_list)):

    plt.subplot(len(covar_list), 1, i+1)

    var = bn.variable(covar_list[i])
    xticks = get_xticks(var)

    plt.grid(True)

    plt.bar(range(len(xticks)), cond_ATE_evo(bn, covar_list[i]), alpha=1)
    #plt.plot(range(len(xticks)), cond_ATE_evo(bn, covar_list[i]))

    plt.xticks(ticks=range(len(xticks)), labels=xticks,
               rotation=30 if var.varType() == 0 else 0)
    plt.ylabel("CATE")

    plt.axhline(y=0, color='r', linestyle='--', linewidth=1)
    plt.title(f"CATE estimation with X = {covar_list[i]}")

plt.subplots_adjust(wspace=0.5, hspace=0.5)
plt.show()
```


CATE estimation with X = lead_time
CATE
0.0
−0.1
−0.2
−0.3
(0.0;9.0[
[9.0;36.0[
[36.0;83.0[
[83.0;162.0[
[162.0;737.0)
CATE estimation with X = is_repeated_guest
CATE
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
0
1
CATE estimation with X = previous_bookings_not_canceled
CATE
0.0
−0.1
−0.2
(0.0;3.4[
[3.4;13.3[
[13.3;30.3[
[30.3;51.2[
[51.2;72.0)
CATE estimation with X = booking_changes
CATE
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
(0.0;1.2[
[1.2;4.1[
[4.1;9.2[
[9.2;15.1[
[15.1;21.0)
CATE estimation with X = days_in_waiting_list
CATE
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
(0.0;33.1[
[33.1;112.2[
[112.2;192.0[
[192.0;290.1[
[290.1;379.0)
CATE estimation with X = required_car_parking_spaces
CATE
0.1
0.0
−0.1
−0.2
0
1
2
3
8
CATE estimation with X = total_of_special_requests
CATE
0.1
0.0
−0.1
−0.2
−0.3
0
1
2
3
4
5



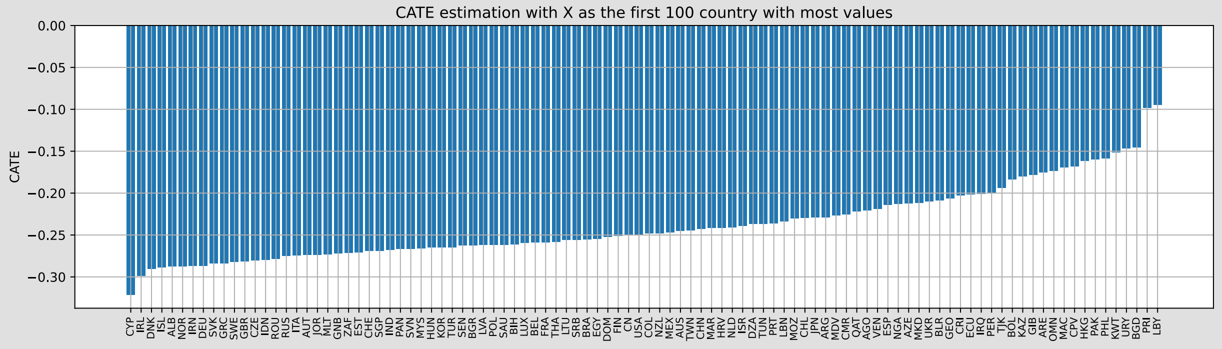


In [26]:

```
country_list = df["country"].value_counts()[:100].index
ATE_country_list = list()

for country in country_list:
    ATE_country_list.append(ATE(bn, {"country":country}))

ATE_country_df = pd.DataFrame(data={"ATE":ATE_country_list}, index=country_list)
ATE_country_df = ATE_country_df.sort_values(by="ATE")
```

In [33]:

```
plt.figure(figsize=(16,4))
plt.bar(ATE_country_df.index, ATE_country_df["ATE"])
plt.xticks(rotation=90, size=8)
plt.ylabel("CATE")
plt.title(f"CATE estimation with X as the first 100 country with most values")
plt.grid(True)
plt.show()
```

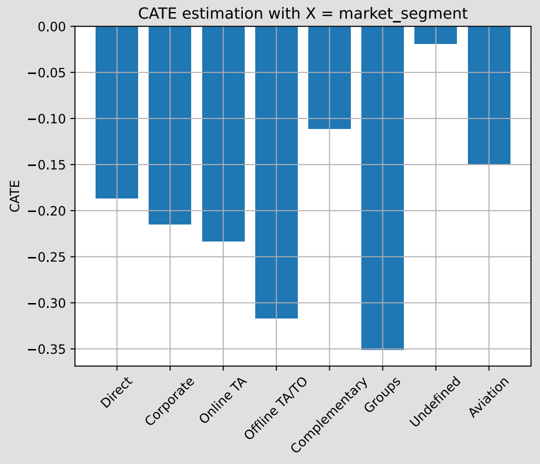


In [28]:

```
market_seg_list = df["market_segment"].unique()
ATE_market_seg__list = list()
for seg in market_seg_list:
    ATE_market_seg__list.append(ATE(bn, {"market_segment":seg}))
```

In [34]:

```
plt.bar(market_seg_list, ATE_market_seg__list)
plt.xticks(rotation=45)
plt.ylabel("CATE")
plt.title(f"CATE estimation with X = market_segment")
plt.grid(True)
plt.show()
```



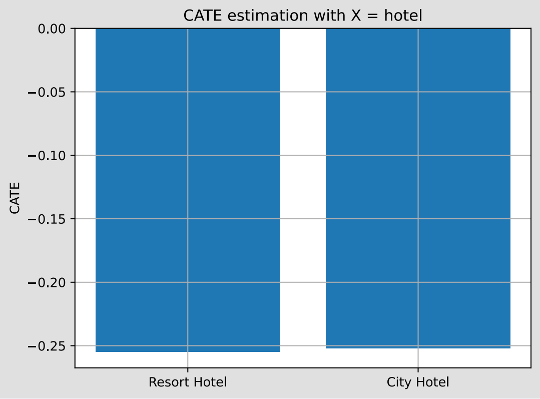
In [30]:

```
hotel_list = df["hotel"].unique()
ATE_hotel_list = list()
```

```
for hotel in hotel_list:
    ATE_hotel_list.append(ATE(bn, {"hotel":hotel}))
```

In [35]:

```
plt.bar(hotel_list, ATE_hotel_list)
plt.ylabel("CATE")
plt.title(f"CATE estimation with X = hotel")
plt.grid(True)
plt.show()
```


CATE estimation with X = hotel
CATE
Resort Hotel
City Hotel