CCUS

October 30, 2024

1 Everything Counts Assignment 1

Gustavo Araujo Costa
LIS FT MASc 2024/2025

Access this notebook on GitHub

PDF generated using nbconvert

1.1 CCUS: Carbon capture, utilization and storage

Covers all large-scale CO2 capture, transport, storage, and utilisation projects commissioned or in planning worldwide.

Source: IEA (2024), CCUS Projects Database

Commentary: https://www.iea.org/commentaries/how-new-business-models-are-boosting-momentum-on-ccus

For feature description, check the README.md file.

1.2 Data cleaning

1.2.1 Import

First, we import the libraries, set style parameters for the plots, import the data, drop the columns that are unimportant and rename the remaining ones.

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

plt.style.use("ggplot")
plt.rcParams["figure.figsize"] = (8, 4)
plt.rcParams["figure.dpi"] = 360
```

[2]:
```
df = pd.read_csv("data/ccus.csv")
df.head()
```

[2]:
```
                                    Project name   ID        Country  \
0  3D DMX ArcelorMittal and IFPEN Dunkirk (full-s…    1         France
1     3D DMX ArcelorMittal and IFPEN Dunkirk 'REUZE'  751          France
```

```
2                            7 Blue Ammonia Facility  1055          Qatar
3                             8Rivers H2 (8RH2) (WY)     3  United States
4                                     Abadi CCS/CCUS   227      Indonesia

                                            Partners Project type  \
0  ArcelorMittal, ifp, Axens, Uetikon, Grassco, b…      Capture
1                    ArcelorMittal, Engie, Infinium          CCU
2  QAFCO, thyssenkrupp Uhde/Consolidated Contract…   Full Chain
3                 8Rivers, Wyoming Energy Authority      Capture
4  Inpex Masela 65%, Shell (trying to find a buye…   Full chain

   Announcement     FID  Operation  Suspension/decommissioning  \
0        2019.0     NaN     2025.0                         NaN
1        2022.0  2024.0     2025.0                         NaN
2        2022.0  2022.0     2026.0                         NaN
3        2022.0     NaN        NaN                         NaN
4        2018.0     NaN     2027.0                         NaN

       Project Status  …  Ref 5 Ref 6  Ref 7  Link 1  Link 2  Link 3 Link 4  \
0             Planned  …    NaN   NaN    NaN  Link 1  Link 2     NaN    NaN
1             Planned  …    NaN   NaN    NaN  Link 1  Link 2     NaN    NaN
2  Under construction  …    NaN   NaN    NaN  Link 1  Link 2     NaN    NaN
3             Planned  …    NaN   NaN    NaN  Link 1     NaN     NaN    NaN
4             Planned  …    NaN   NaN    NaN  Link 1  Link 2  Link 3    NaN

  Link 5 Link 6 Link 7
0    NaN    NaN    NaN
1    NaN    NaN    NaN
2    NaN    NaN    NaN
3    NaN    NaN    NaN
4    NaN    NaN    NaN

[5 rows x 31 columns]
```

[3]:
```
df.columns
```

[3]:
```
Index(['Project name', 'ID', 'Country', 'Partners', 'Project type',
       'Announcement', 'FID', 'Operation', 'Suspension/decommissioning',
       'Project Status', 'Project phase', 'Announced capacity (Mt CO2/yr)',
       'Estimated capacity by IEA (Mt CO2/yr)', 'Sector', 'Fate of carbon',
       'Part of CCUS hub', 'Region', 'Ref 1', 'Ref 2', 'Ref 3', 'Ref 4',
       'Ref 5', 'Ref 6', 'Ref 7', 'Link 1', 'Link 2', 'Link 3', 'Link 4',
       'Link 5', 'Link 6', 'Link 7'],
      dtype='object')
```

[4]:
```
df = df.drop(
    columns=[
```

```
        "Suspension/decommissioning",
        "Project phase",
        "FID",
        "ID",
        "Operation",
        "Partners",
        "Part of CCUS hub",
        "Ref 1",
        "Ref 2",
        "Ref 3",
        "Ref 4",
        "Ref 5",
        "Ref 6",
        "Ref 7",
        "Link 1",
        "Link 2",
        "Link 3",
        "Link 4",
        "Link 5",
        "Link 6",
        "Link 7",
    ]
)

df.iloc[0]
```

[4]:
```
Project name                                    3D DMX ArcelorMittal and IFPEN Dunkirk
(full-s…
Country
France
Project type
Capture
Announcement
2019.0
Project Status
Planned
Announced capacity (Mt CO2/yr)
0.7
Estimated capacity by IEA (Mt CO2/yr)
0.7
Sector                                                                            Iron
and steel
Fate of carbon
Unknown/unspecified
Region
Europe
Name: 0, dtype: object
```

[5]:
```
df = df.rename(
    columns={
        "Project name": "name",
        "Country": "country",
        "Project type": "type",
        "Announcement": "year",
        "Project Status": "status",
        "Announced capacity (Mt CO2/yr)": "capacity_ann",
        "Estimated capacity by IEA (Mt CO2/yr)": "capacity_est",
        "Sector": "sector",
        "Region": "region",
        "Fate of carbon": "fate",
    }
)

# explanations for each feature are in the original excel file
df = df[
    [
        "name",
        "status",
        "region",
        "country",
        "sector",
        "type",
        "fate",
        "year",
        "capacity_ann",
        "capacity_est",
    ]
]
df.iloc[0]
```

[5]:
```
name            3D DMX ArcelorMittal and IFPEN Dunkirk (full-s…
status                                                   Planned
region                                                    Europe
country                                                   France
sector                                            Iron and steel
type                                                     Capture
fate                                        Unknown/unspecified
year                                                      2019.0
capacity_ann                                                 0.7
capacity_est                                                 0.7
Name: 0, dtype: object
```

1.2.2 Altering columns: Project Type

In this part, we fix the ‘Full Chain’/‘Full chain’ capitalization issue.

[6]:
```python
df["type"].value_counts()
```

[6]:
```
type
Capture       352
Full chain    144
Storage       134
T&S            88
Transport      63
CCU            55
Full Chain      8
Name: count, dtype: int64
```

[7]:
```python
def fix_full_chain(value: str) -> str:
    if "Full chain" in value:
        return "Full Chain"
    else:
        return value


df["type"] = df["type"].apply(fix_full_chain)
df["type"].value_counts()
```

[7]:
```
type
Capture       352
Full Chain    152
Storage       134
T&S            88
Transport      63
CCU            55
Name: count, dtype: int64
```

1.2.3 Altering columns: Country and Region

While there are some `country` entries which are not standardized (`Australia-Japan`), they are not that prevalent as to affect the analysis. The same is the case for the `region` feature.

[8]:
```python
df["country"].value_counts()
```

[8]:
```
country
United States                                      293
United Kingdom                                      92
Canada                                              74
Norway                                              34
Australia                                           33
                                                 …
Lithuania                                            1
New Zealand                                          1
```

```
Papua New Guinea                                        1
Lybia                                                   1
Belgium, Germany, Netherlands, Switzerland, USA         1
Name: count, Length: 66, dtype: int64
```

[9]:
```
df["region"].value_counts()
```

[9]:
```
region
North America                                         368
Europe                                                310
Other Asia Pacific                                     86
Australia and New Zealand                              37
Middle East                                            21
Eurasia                                                 7
Central and South America                               5
Unknown                                                 4
Africa                                                  4
Other Asia Pacific - Australia and New Zealand          2
Name: count, dtype: int64
```

1.2.4 Convert appropriate columns to category dtype

In this section, we convert some columns to the category dtype. These columns were selected by going through each of the columns with the `value_counts()` method to check if they had categorical data. Although not particularly relevant in this case, we also see a ~3x reduction in memory usage.

[10]:
```
df.info(memory_usage="deep")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 844 entries, 0 to 843
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   name          844 non-null    object
 1   status        844 non-null    object
 2   region        844 non-null    object
 3   country       844 non-null    object
 4   sector        844 non-null    object
 5   type          844 non-null    object
 6   fate          844 non-null    object
 7   year          824 non-null    float64
 8   capacity_ann  614 non-null    object
 9   capacity_est  645 non-null    float64
dtypes: float64(2), object(8)
memory usage: 468.1 KB
```

[11]:
```python
category_cols = [
    "country",
    "type",
    "status",
    "sector",
    "fate",
    "region",
]

df[category_cols] = df[category_cols].astype("category")
```

[12]:
```python
df.info(memory_usage="deep")
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 844 entries, 0 to 843
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   name          844 non-null    object
 1   status        844 non-null    category
 2   region        844 non-null    category
 3   country       844 non-null    category
 4   sector        844 non-null    category
 5   type          844 non-null    category
 6   fate          844 non-null    category
 7   year          824 non-null    float64
 8   capacity_ann  614 non-null    object
 9   capacity_est  645 non-null    float64
dtypes: category(6), float64(2), object(2)
memory usage: 148.4 KB
```

1.2.5 Altering columns: capacity_ann

`capacity_ann` it the only column which needs to be modified. This is necessary because there are 106 entries which have ranges instead of numbers. This makes it so the dtype of the column is wrong, which interrupts further analysis.

First, we drop the entries with missing data announcement data, which are about 27% of the data. While this might introduce some bias regarding the availability of that data, we judge it to be necessary. Dropping these entries conveniently removes the 23% of projects which have no estimated capacity as well.

We save this as a new dataframe so the whole data is still available for categorical feature description, but we have the cleaned data for numerical analysis.

[13]:
```python
missing_announcement = df["capacity_ann"].isna().sum() / df.shape[0] * 100
print(f"Around {missing_announcement:.2f}% of the data has no announced␣
↪capacity")
```

```
Around 27.25% of the data has no announced capacity
```

[14]:
```python
missing_estimated = df["capacity_est"].isna().sum() / df.shape[0] * 100
print(f"Around {missing_estimated:.2f}% of the data has no estimated capacity")
```

```
Around 23.58% of the data has no estimated capacity
```

[15]:
```python
df_77 = df.dropna(subset=["capacity_ann"])
```

To substitute a range for its mean, we should have a reasonable argument that the mean is representative of the range. We do this by checking the distribution of the ranges. We will use this data shortly.

[16]:
```python
def range_size(value: str) -> float:
    if "-" not in value:
        return float(value)

    arr = value.split("-")
    a = float(arr[0].strip())
    b = float(arr[1].strip())
    return b - a


ranges = df_77["capacity_ann"].apply(range_size)
```

Here we find two outliers (250 and 120), which are dropped from the descriptive statistics. This also sets indices 635 and 676 as noteworthy, which will be important later.

[17]:
```python
ranges.sort_values(ascending=False).head()
```

[17]:
```
635    250.0
676    120.0
794     30.0
563     30.0
773     30.0
Name: capacity_ann, dtype: float64
```

[18]:
```python
ranges.drop([635, 676]).describe()
```

[18]:
```
count    612.000000
mean       2.479724
std        4.076815
min       -5.000000
25%        0.300000
50%        1.000000
75%        2.962500
max       30.000000
Name: capacity_ann, dtype: float64
```

This code detects if the entry is a range, splits it, converts it into a number, gets the mean of the range, and returns it.

```
[19]: def range_cleanup(value: str) -> float:
          if "-" not in value:
              return float(value)

          arr = value.split("-")
          a = float(arr[0].strip())
          b = float(arr[1].strip())
          return (a + b) / 2


      df_77["capacity_ann"] = df_77["capacity_ann"].apply(range_cleanup)
      df_77["capacity_ann"].sample(5)
```

```
/tmp/ipykernel_5846/1303587104.py:11: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_77["capacity_ann"] = df_77["capacity_ann"].apply(range_cleanup)
```

```
[19]: 285     0.8
      223     1.4
      32     14.0
      2       1.5
      489     1.7
      Name: capacity_ann, dtype: float64
```

```
[20]: df_77["capacity_ann"].drop([635, 676]).describe()
```

```
[20]: count    612.000000
      mean       2.796284
      std        4.425264
      min        0.000000
      25%        0.400000
      50%        1.200000
      75%        3.000000
      max       30.000000
      Name: capacity_ann, dtype: float64
```

The resulting data has mean `2.8` (std `4.4`).

The ranges which were altered have mean `2.4` (std `4`).

Since the mean of the ranges is inside the standard deviation of the data, we assume the substituting the range for the mean does not distort the data. While this is debatable, this is also not the point of this assignment, so let's move on.

The feature `capacity_ann` is now tractable for numerical analysis.

1.2.6 New feature: capacity_diff

This also makes it possible for us to add a new feature: the difference between the announced capacity and the estimated capacity.

[21]:
```
df_77["capacity_diff"] = df_77["capacity_ann"] - df_77["capacity_est"]

df_77["capacity_diff"].describe()
```

```
/tmp/ipykernel_5846/4224938376.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_77["capacity_diff"] = df_77["capacity_ann"] - df_77["capacity_est"]
```

[21]:
```
count    614.000000
mean      -0.068950
std        0.749446
min      -10.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        5.000000
Name: capacity_diff, dtype: float64
```

Given that the minimum value is `-10`, the maximum is `5`, the mean is `-0.06` and the standard deviation `0.7`, we can assume that the difference between estimated and announced capacity is not relevant in most cases.

This is all saved in the `df_77` DataFrame to be used later.

1.2.7 Missing data

These are the missing values by column:

[22]:
```
df.isna().sum().sort_values(ascending=False)
```

[22]:
```
capacity_ann    230
capacity_est    199
year             20
name              0
status            0
region            0
type              0
```

```
sector            0
country           0
fate              0
dtype: int64
```

Since it is only about 2% of the original sample, entries without an announcement year entry are dropped.

[23]:
```
df = df.dropna(subset=["year"])
```

In this way, all missing values are removed from the sample (besides the missing capacity data, which we already talked about)

1.3 Descriptive Statistics

[24]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 824 entries, 0 to 842
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   name          824 non-null    object
 1   status        824 non-null    category
 2   region        824 non-null    category
 3   country       824 non-null    category
 4   sector        824 non-null    category
 5   type          824 non-null    category
 6   fate          824 non-null    category
 7   year          824 non-null    float64
 8   capacity_ann  597 non-null    object
 9   capacity_est  628 non-null    float64
dtypes: category(6), float64(2), object(2)
memory usage: 41.2+ KB
```

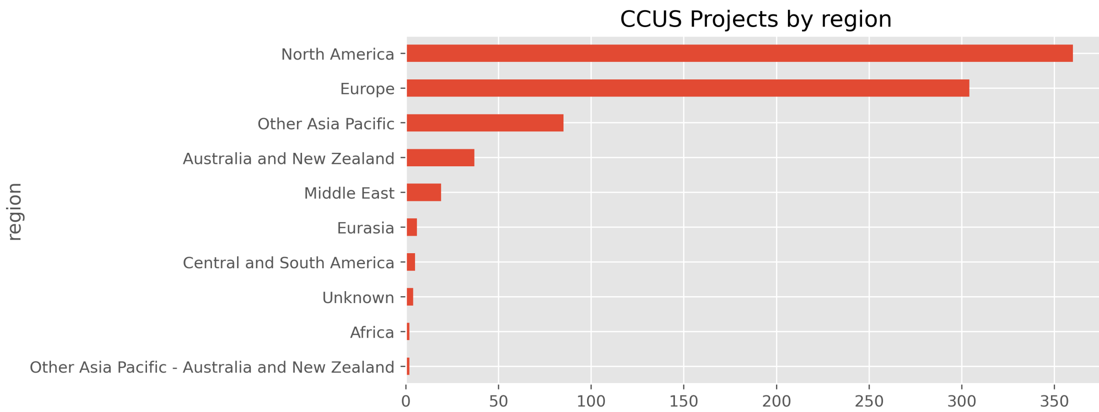
1.3.1 Categorical variables

Here, we do some descriptive statistics of the categorical features:

- Region
- Country
- Fate of carbon
- Sector
- type
- Project status

[25]:
```
df["region"].value_counts().sort_values(ascending=True).plot.barh()
plt.title("CCUS Projects by region")
```

[25]: Text(0.5, 1.0, 'CCUS Projects by region')

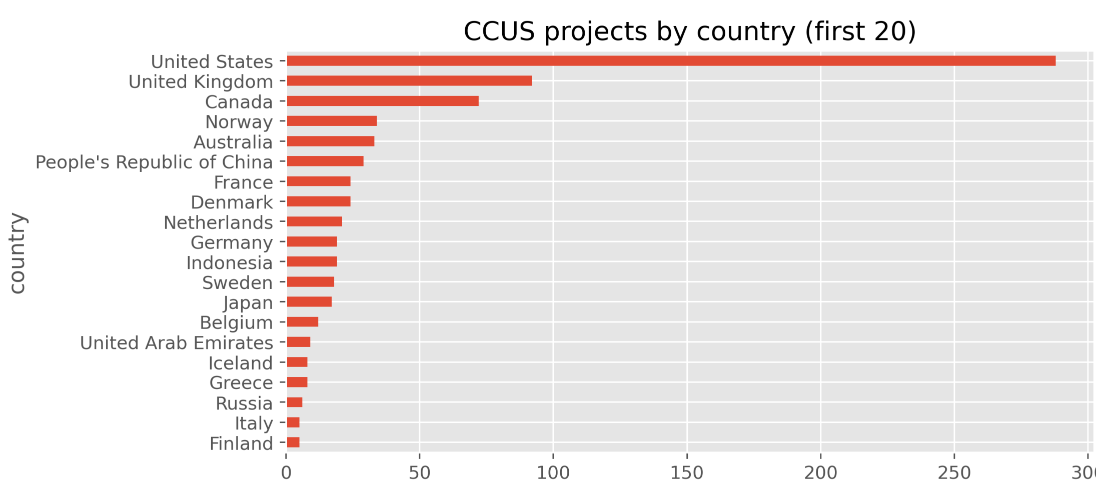



```
[26]: df_rows_count = df.shape[0]
europe_counts = (df["region"] == "Europe").sum()
na_counts = (df["region"] == "North America").sum()
region_percentage = (europe_counts + na_counts) / df_rows_count
print(
    f"Europe and North America account for {region_percentage * 100:.2f}% of␣
 ↪total entries"
)
```

Europe and North America account for 80.58% of total entries

```
[27]: df["country"].value_counts().sort_values(ascending=True).tail(20).plot.barh()
plt.title("CCUS projects by country (first 20)")
```

[27]: Text(0.5, 1.0, 'CCUS projects by country (first 20)')

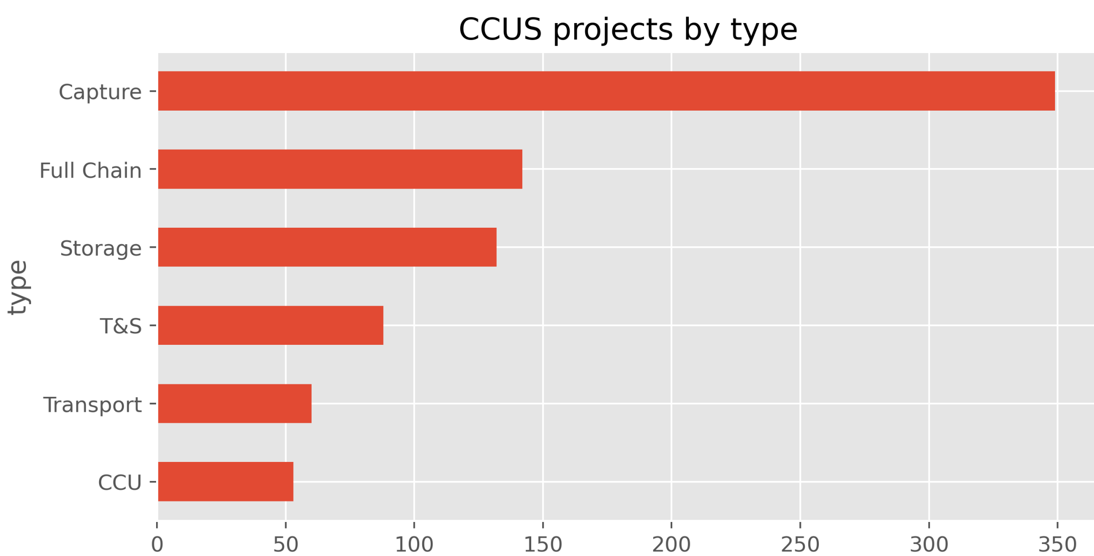


[28]:
```python
df_rows_count = df.shape[0]
us_counts = (df["country"] == "United States").sum()
country_percentage = us_counts / df_rows_count
print(f"US accounts for {country_percentage * 100:.2f}% of total entries")
```

```
US accounts for 34.95% of total entries
```

[29]:
```python
df["type"].value_counts().sort_values().plot.barh()
plt.title("CCUS projects by type")
```

[29]: Text(0.5, 1.0, 'CCUS projects by type')



[30]:
```python
df_rows_count = df.shape[0]
capture_counts = ((df["type"] == "Capture") | (df["type"] == "Full Chain")).
 ↪sum()
type_percentage = capture_counts / df_rows_count
print(f"Capture projects account for {type_percentage * 100:.2f}% of total␣
 ↪entries")
```

```
Capture projects account for 59.59% of total entries
```

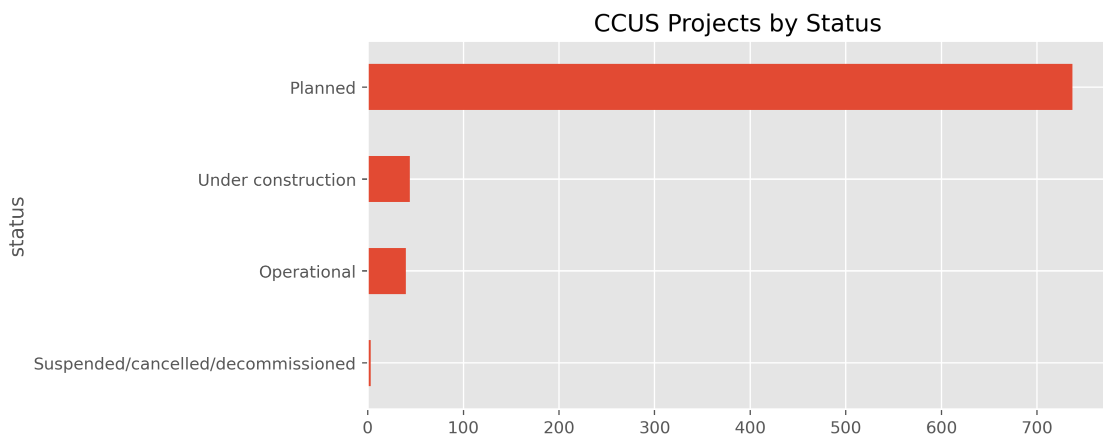
[31]:
```python
df_rows_count = df.shape[0]
storage_counts = (
    (df["type"] == "Storage") | (df["type"] == "Full Chain") | (df["type"] ==␣
 ↪"T&S")
).sum()
type_percentage = storage_counts / df_rows_count
```

```
print(f"Storage projects account for {type_percentage * 100:.2f}% of total␣
  ↪entries")
```

```
Storage projects account for 43.93% of total entries
```

[32]:
```
df["status"].value_counts().sort_values().plot.barh()
plt.title("CCUS Projects by Status")
```

[32]:
```
Text(0.5, 1.0, 'CCUS Projects by Status')
```



[33]:
```
df_rows_count = df.shape[0]
planned_counts = (df["status"] == "Planned").sum()
status_percentage = planned_counts / df_rows_count
print(f"Planned status accounts for {status_percentage * 100:.2f}% of total␣
  ↪entries")
```

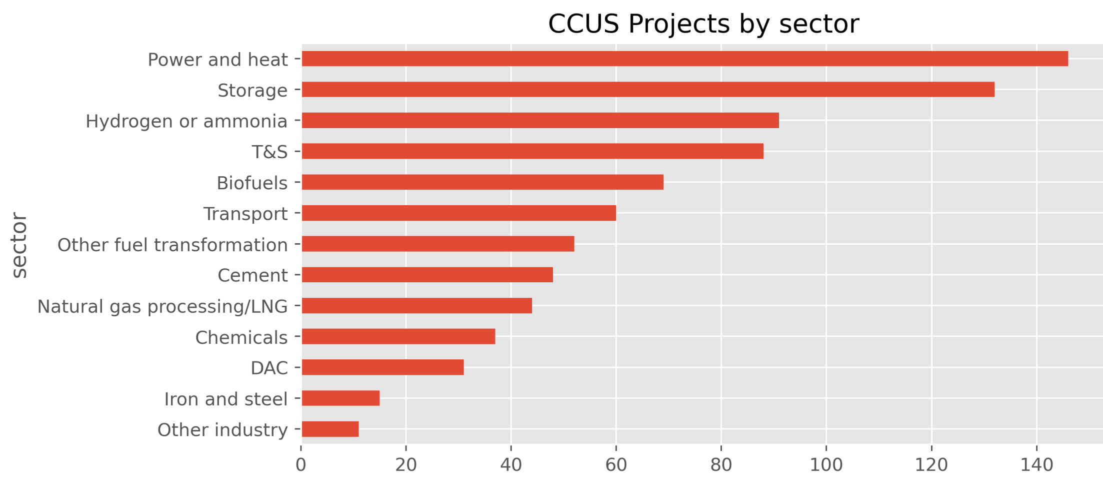
```
Planned status accounts for 89.44% of total entries
```

[34]:
```
df_rows_count = df.shape[0]
op_counts = (df["status"] == "Operational").sum()
status_percentage = op_counts / df_rows_count
print(
    f"Operational status accounts for {status_percentage * 100:.2f}% of total␣
  ↪entries"
)
```

```
Operational status accounts for 4.85% of total entries
```

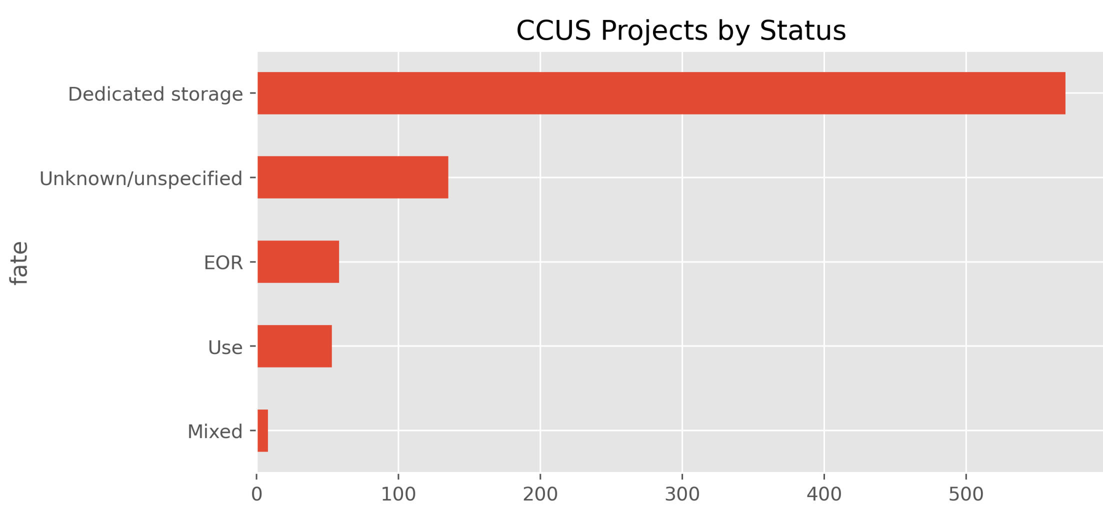
[35]:
```
df["sector"].value_counts().sort_values(ascending=True).plot.barh()
plt.title("CCUS Projects by sector")
```

[35]:
```
Text(0.5, 1.0, 'CCUS Projects by sector')
```



[36]:
```
df["fate"].value_counts().sort_values().plot.barh()
plt.title("CCUS Projects by Status")
```

[36]: Text(0.5, 1.0, 'CCUS Projects by Status')



[37]:
```
df_rows_count = df.shape[0]
fate_counts = (df["fate"] == "Dedicated storage").sum()
status_percentage = fate_counts / df_rows_count
print(f"Storage accounts for {status_percentage * 100:.2f}% of total entries")
```

Storage accounts for 69.17% of total entries

1.3.2 Insights

- Projects are mainly based in the United States (34.95%)
- If we consider Europe and North America, that number rises to **80.85%**
- Most projects (**86.26%**) are in the planning stage.
- While most projects are concerned with capture (59.59%), there is some diversity there.
- The fate of carbon of 69.17% of projects is storage, but only 43% of projects plan on storing the carbon.

With this, we have a median picture of a CCUS project: a company in Europe or the US that has plans to capture carbon for them or somebody else to store it. This makes sense considering the US's plan to become an environmental innovation center. While China is investing in electric vehicles, it does not seem to be investing in CCUS.

There might be a pentiful supply of captured CO2 looking for storage or utilization, which is a potential niche in the market to be explored. This is, however, predictive, since most of the projects are still in the planning stage.

1.3.3 Numerical features

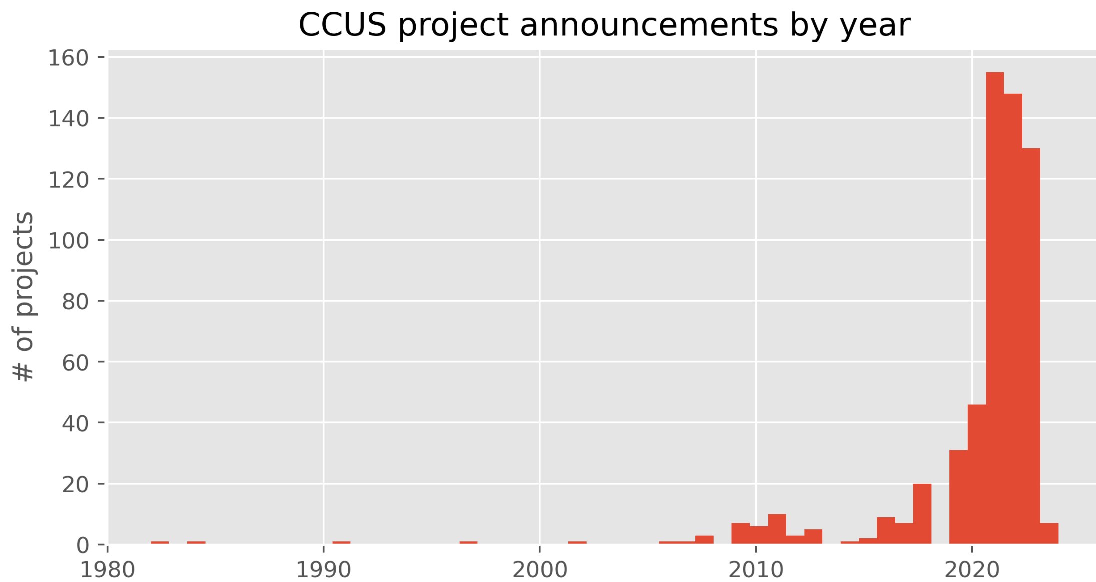
Here, we do some descriptive statistics of the numerical features:

- `year`: year of project announcement
- `capacity_ann`: Announced capacity (Mt CO2/yr)
- `capacity_est`: Estimated capacity by IEA (Mt CO2/yr)
- `capacity_diff`: difference between announced and estimated capacity

We use the df_77 for this.

[38]:
```
df_77["year"].hist(bins=50)
plt.ylabel("# of projects")
plt.title("CCUS project announcements by year")
```

[38]:
```
Text(0.5, 1.0, 'CCUS project announcements by year')
```

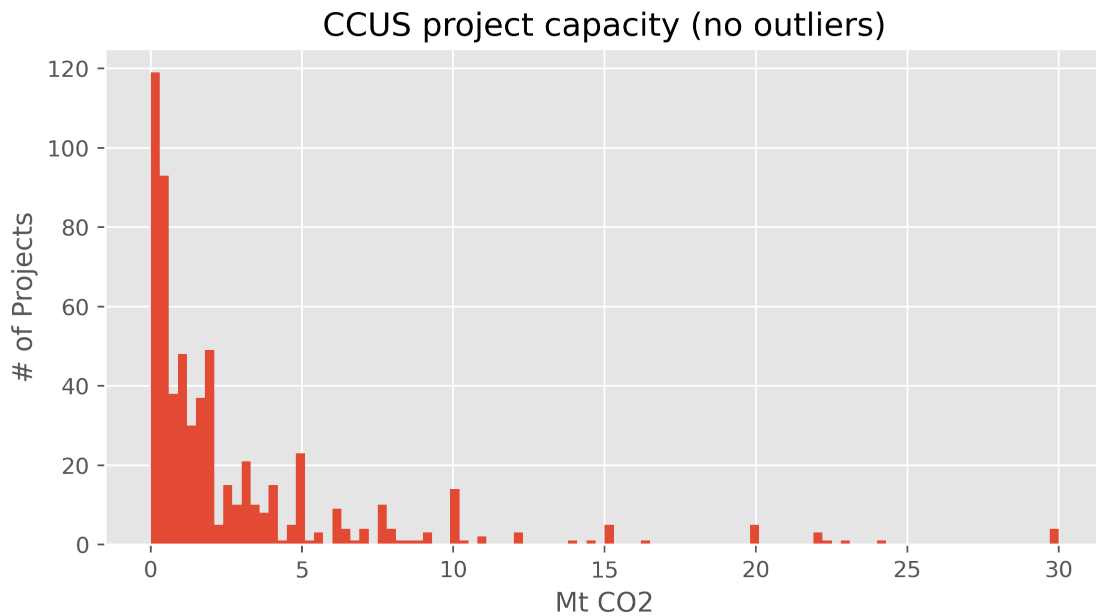


[39]:
```
year_p = (155 + 148 + 130) / df_77.shape[0]
print(f"{year_p * 100:.2f}% of projects announced in 2021-2023")
```

70.52% of projects announced in 2021-2023

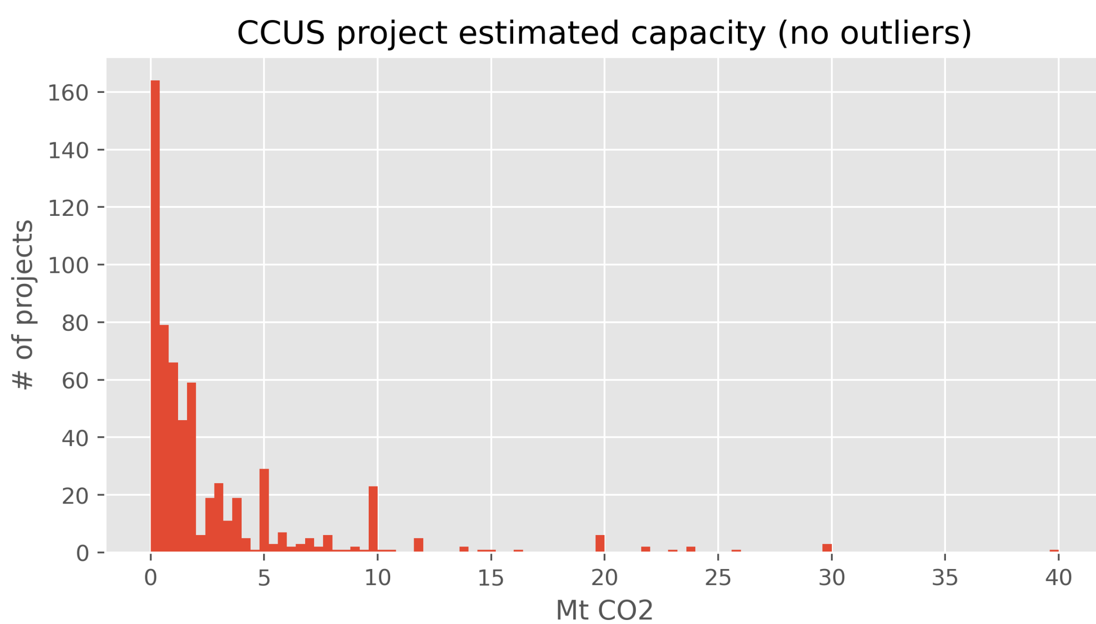
[40]:
```
df_77["capacity_ann"].drop([635, 676]).hist(bins=100)
plt.xlabel("Mt CO2")
plt.ylabel("# of Projects")
plt.title("CCUS project capacity (no outliers)")
```

[40]: Text(0.5, 1.0, 'CCUS project capacity (no outliers)')



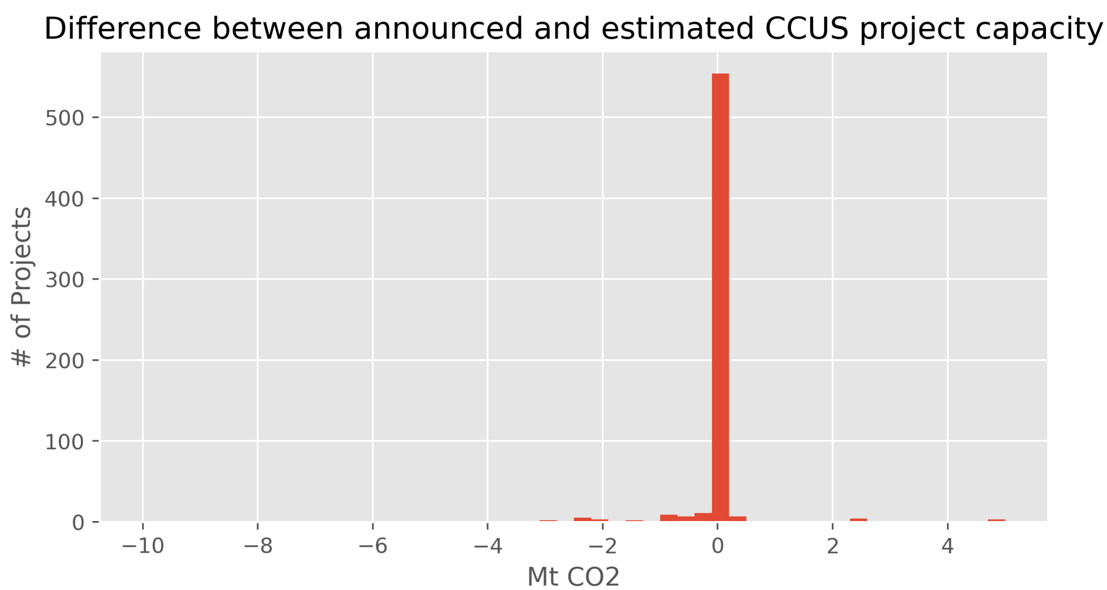
[41]:
```
df_77["capacity_est"].drop([635, 676]).hist(bins=100)
plt.xlabel("Mt CO2")
plt.ylabel("# of projects")
plt.title("CCUS project estimated capacity (no outliers)")
```

[41]:
```
Text(0.5, 1.0, 'CCUS project estimated capacity (no outliers)')
```



[42]:
```
df_77["capacity_diff"].hist(bins=50)
plt.xlabel("Mt CO2")
plt.ylabel("# of Projects")
plt.title("Difference between announced and estimated CCUS project capacity")
```

[42]:
```
Text(0.5, 1.0, 'Difference between announced and estimated CCUS project
capacity')
```



1.3.4 Insights

The data continues being mostly homogenous, with *70%* of projects being announced in 2021-2023

1.3.5 Outliers

Obs: I used df_77 instead of df here because the df_77 table returns more results than the whole table, which makes no sense.

[43]:
```
df_77[df_77["status"] == "Suspended/cancelled/decommissioned"]
```

[43]:
```
                                     name                              status  \
433  Illinois Basin Decatur Project (IL)  Suspended/cancelled/decommissioned
437                             In Salah  Suspended/cancelled/decommissioned
462                 Kemper county CCUS (MS)  Suspended/cancelled/decommissioned

            region        country                        sector        type  \
433  North America  United States                      Biofuels  Full Chain
437         Africa        Algeria  Natural gas processing/LNG  Full Chain
462  North America  United States                Power and heat  Full Chain
```

```
                 fate    year  capacity_ann  capacity_est  capacity_diff
433  Dedicated storage  2009.0          0.33          0.33            0.0
437  Dedicated storage     NaN          0.50          0.50            0.0
462                EOR     NaN          3.00          3.00            0.0
```

[44]:
```
df_77[df_77["region"] == "Africa"]
```

[44]:
```
                         name                              status  region  \
359  Great Carbon Valley DAC                              Planned  Africa
437                 In Salah  Suspended/cancelled/decommissioned  Africa
663       Project Hummingbird                             Planned  Africa
749            Structure A&E                              Planned  Africa

     country                       sector        type               fate  \
359    Kenya                          DAC  Full Chain  Dedicated storage
437  Algeria  Natural gas processing/LNG  Full Chain  Dedicated storage
663    Kenya                          DAC  Full Chain  Dedicated storage
749    Lybia  Natural gas processing/LNG  Full Chain  Dedicated storage

       year  capacity_ann  capacity_est  capacity_diff
359  2023.0         1.000         1.000            0.0
437     NaN         0.500         0.500            0.0
663     NaN         0.001         0.001            0.0
749  2023.0         1.600         1.600            0.0
```

Here, we see that the oversized projects are both Transport projects, which explains their size in comparison to the other ones.

[45]:
```
df_77[df_77["capacity_ann"] > 100]
```

[45]:
```
                                                name   status         region  \
635  Port of Corpus Christi-Mississippi pipeline (TX)  Planned  North America
676                       Project WyoTCH pipeline (WY)  Planned  North America

           country     sector       type                 fate    year  \
635  United States  Transport  Transport  Unknown/unspecified  2023.0
676  United States  Transport  Transport  Unknown/unspecified  2023.0

     capacity_ann  capacity_est  capacity_diff
635         250.0         250.0            0.0
676         120.0         120.0            0.0
```

The two biggest non-transport projects are from the UK, which is somewhat unexpected.

[46]:
```
# df_77["capacity_ann"].drop([635, 676]).sort_values(ascending=False).head(10)

df_77.drop([635, 676])[df_77["capacity_ann"] > 25]
```

```
/tmp/ipykernel_5846/2164995681.py:3: UserWarning: Boolean Series key will be
reindexed to match DataFrame index.
  df_77.drop([635, 676])[df_77["capacity_ann"] > 25]
```

[46]:

```
                                        name   status  region  \
319  Fluxys-Equinor Belgium-Norway Trunk Line  Planned  Europe
563                      North Sea CO2 corridor  Planned  Europe
773            The Bluestreak CO2 Joint Venture  Planned  Europe
794             UK Poseidon CCS project phase 2  Planned  Europe

              country     sector       type               fate    year  \
319   Belgium-Norway  Transport  Transport  Dedicated storage  2022.0
563  Belgium-Germany  Transport  Transport  Dedicated storage  2023.0
773   United Kingdom        T&S        T&S  Dedicated storage  2023.0
794   United Kingdom    Storage    Storage  Dedicated storage  2023.0

     capacity_ann  capacity_est  capacity_diff
319          30.0          40.0          -10.0
563          30.0          30.0            0.0
773          30.0          30.0            0.0
794          30.0          30.0            0.0
```

Here we see the older projects are all full chain, which makes sense since there was no previous infrastructure to accomodate projects for a specific niche. They alse have much higher capacity than the median project in the data. This is talked about in the commentary: "historically, oil and gas companies have been leaders in CCUS development". They are also for EOR (enhanced oil recovery) projects, which means they are not necessarily interested in reducing carbon emissions per se. They are also all still operational.

[47]:

```python
df_77[df_77["year"] < 2000]
```

[47]:

```
                                                     name       status  \
294                                  Enid fertiliser (OK)  Operational
360  Great Plains Synfuel Plant (ND) Weyburn-Midale…  Operational
476  Labarge Shute Creek Gas Processing Plant origi…  Operational
735                                              Sleipner  Operational

            region        country                       sector       type  \
294  North America  United States                    Chemicals  Full Chain
360  North America  United States   Other fuel transformation  Full Chain
476  North America  United States  Natural gas processing/LNG  Full Chain
735         Europe         Norway  Natural gas processing/LNG  Full Chain

                  fate    year  capacity_ann  capacity_est  capacity_diff
294                EOR  1982.0          0.68          0.68            0.0
360                EOR  1997.0          3.00          3.00            0.0
476                EOR  1984.0          3.50          3.50            0.0
735  Dedicated storage  1991.0          1.00          1.00            0.0
```

1.4 Key insights

- Interesting projects might include
  - Bluestreak
  - Poseidon
  - Sleipner

1.5 Numerical data

[48]:
```
import statsmodels.formula.api as smf
import statsmodels.api as sm

df_n = df_77.drop([635, 676])  # drop outliers
```

Since both capacity measures have 98% correlation, we can use either for the plots

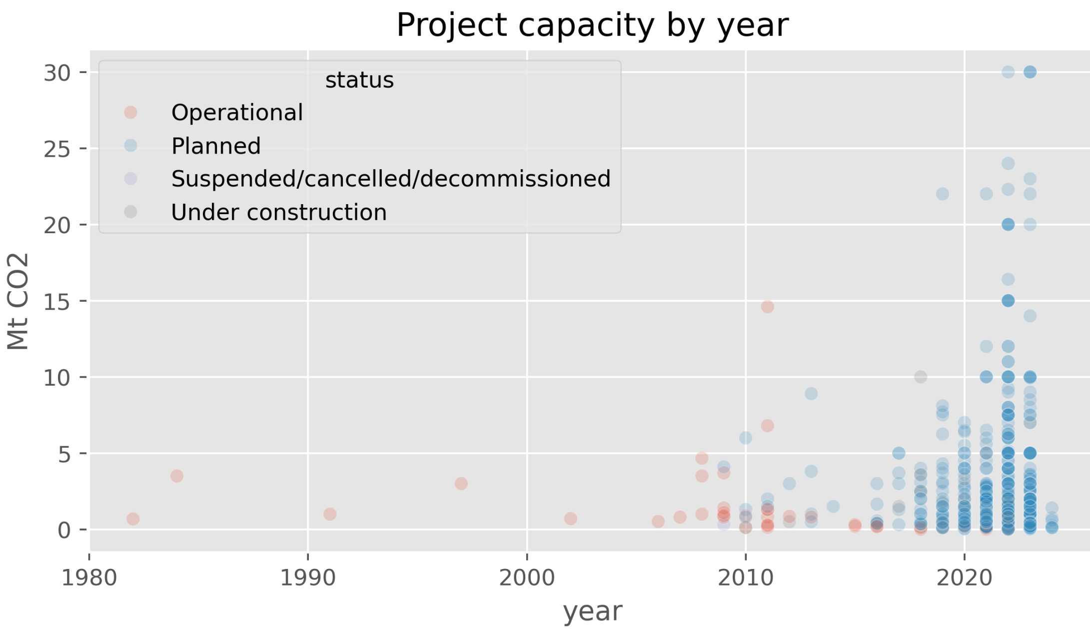
[49]:
```
df_n[["capacity_ann", "capacity_est"]].corr()
```

[49]:

	capacity_ann	capacity_est
capacity_ann	1.000000	0.987177
capacity_est	0.987177	1.000000

[ ]:
```
sns.scatterplot(
    x="year",
    y="capacity_ann",
    data=df_n,
    alpha=0.2,
    hue="status",
)
plt.ylabel("Mt CO2")
plt.title("Project capacity by year");
```

[ ]:
```
Text(0.5, 1.0, 'Project capacity by year')
```

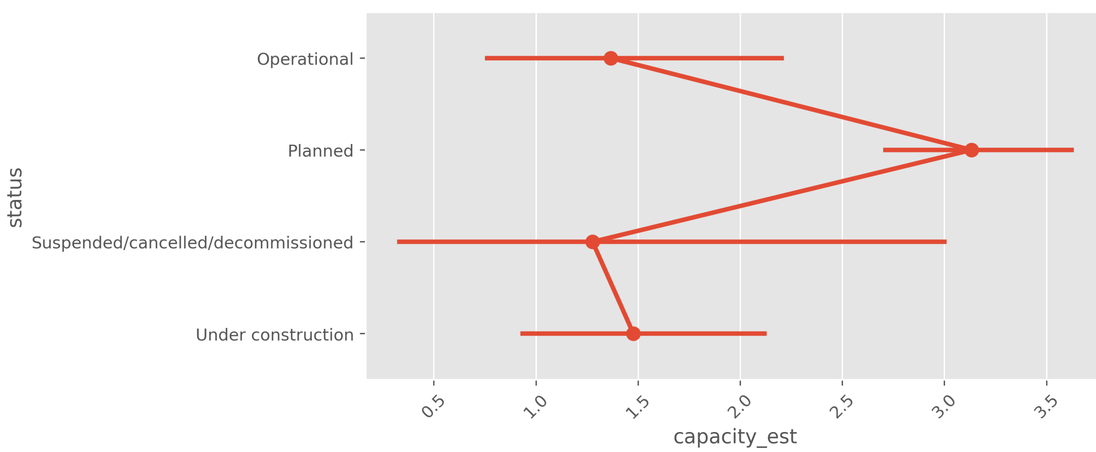


This plot shows the concentration of projects after 2020 and how most of them are in the planned category

1.5.1 Status x Capacity

[51]:
```
iv = "status"
dv = "capacity_est"

sns.pointplot(x=dv, y=iv, data=df_n)
plt.xticks(rotation=45);
```



[52]:
```
# aov = smf.ols(f"{dv} ~ {iv}", data=df_n).fit()
# aov.summary()
```

[53]:
```
df_n["capacity_ann"][df_n["status"] == "Planned"].describe()
```

[53]:
```
count    517.000000
mean       3.060191
std        4.679400
min        0.000000
25%        0.425000
50%        1.400000
75%        3.550000
max       30.000000
Name: capacity_ann, dtype: float64
```

[54]:
```
df_n["capacity_ann"][df_n["status"] != "Planned"].describe()
```

[54]:
```
count    95.000000
mean      1.360074
std       2.149928
min       0.001000
25%       0.225000
50%       0.515000
75%       1.500000
max      14.600000
Name: capacity_ann, dtype: float64
```

- Planned: mean 3.0 and std 4.6
- Others: mean 1.4 and std 2.5

Sounds like the projects will, on average, double their capacity to capture carbon. This might reflect better tech, more interest or something else.

Let's test if this difference is statistically significant.

1.5.2 Null hypothesis significance test

H0: meanplanned - meanother = 0

HA: meanplanned - meanother =/= 0

[55]:
```
import statsmodels.stats.weightstats as st

series_a = df_n["capacity_ann"][df_n["status"] == "Planned"]
series_b = df_n["capacity_ann"][df_n["status"] != "Planned"]

cm = st.CompareMeans(
    st.DescrStatsW(series_a),
    st.DescrStatsW(series_b),
```

```
)
```

[56]:
```
cm.summary()
```

[56]:

	coef	std err	t	P> |t|	[0.025	0.975]
subset #1	1.7001	0.490	3.473	0.001	0.739	2.662

[57]:
```
_, p, _ = cm.ttest_ind()
confint_low, confint_high = cm.tconfint_diff()
print(f"CI [{confint_low:.2f}, {confint_high:.2f}]")
print(f"p = {p:.3f}")
```

```
CI [0.74, 2.66]
p = 0.001
```

Since:

- the confidence interval does not cross zero and
- the p value is less than 0.05,

we can say that the difference between these means is statistically significant.

Thus, we **reject the null hypothesis** that there is no difference between the means of the CCUS projects that are planned and the ones which are already operational, under construction or decomissioned.

Of course, the IEA says that these are all the large-scale CCUS projects that exist, which means that we are working not with a sample, but the whole population. If that is the case, no statistical test is necessary – the means are simply different. But if we don't believe they can track every single project (and they have left many out for a variety of reasons), doing this analysis might be prudent either way.

[58]:
```
# sns.pointplot(x="type", y="capacity_ann", data=df_n)
# plt.xticks(rotation=45);
```

1.6 Conclusion

This project showcases data cleaning, feature engineering, descriptive statistics and inferential statistics. It also confers some insights to someone who might be interested in joining the CCUS market.

- **80%+** CCUS projects are based in Europe and North America
- **85%+** CCUS projects are in the planning stage.
- There are more projects planning on capturing the carbon for storage than there are storage projects.
- Projects being planned today have higher capacity than projects that are operational or being built.