CCUS

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1 Everything Counts Assignment 1

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1.1 CCUS: Carbon capture, utilization and storage

This dataset 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
- rename and reorder the remaining columns.

[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"] = 300
```

[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]:
```python
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",
    }
)

# reorder columns
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]:
```
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]:
```
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]:
```
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 announced capacity 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_27812/1303587104.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]:
```
358     0.165
296    10.000
213     2.000
761     1.270
793     8.500
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 capacity data have mean `2.8` (std `4.4`).

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

Since the mean of the ranges is smaller than 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.

By transforming the reported ranges into numbers, the `capacity_ann` feature 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_27812/4224938376.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(memory_usage='deep')
```

```
<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: 151.5 KB
```

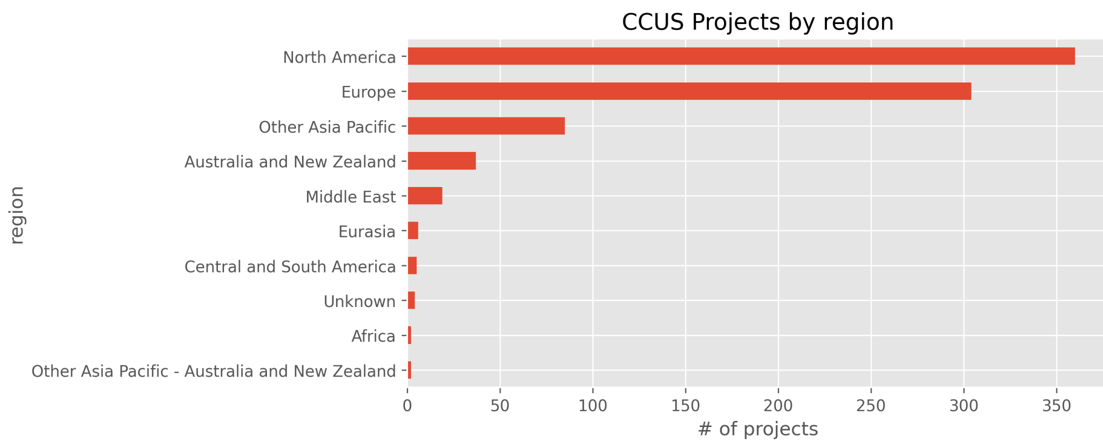
1.3.1 Categorical variables

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

- Region

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

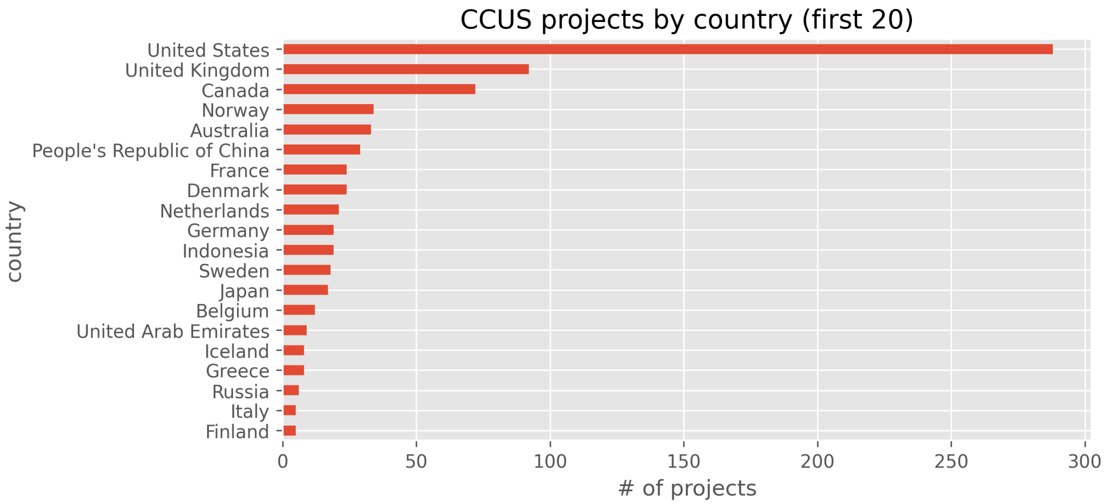
[25]:
```
df["region"].value_counts().sort_values(ascending=True).plot.barh()
plt.xlabel("# of projects")
plt.title("CCUS Projects by region");
```



[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
```

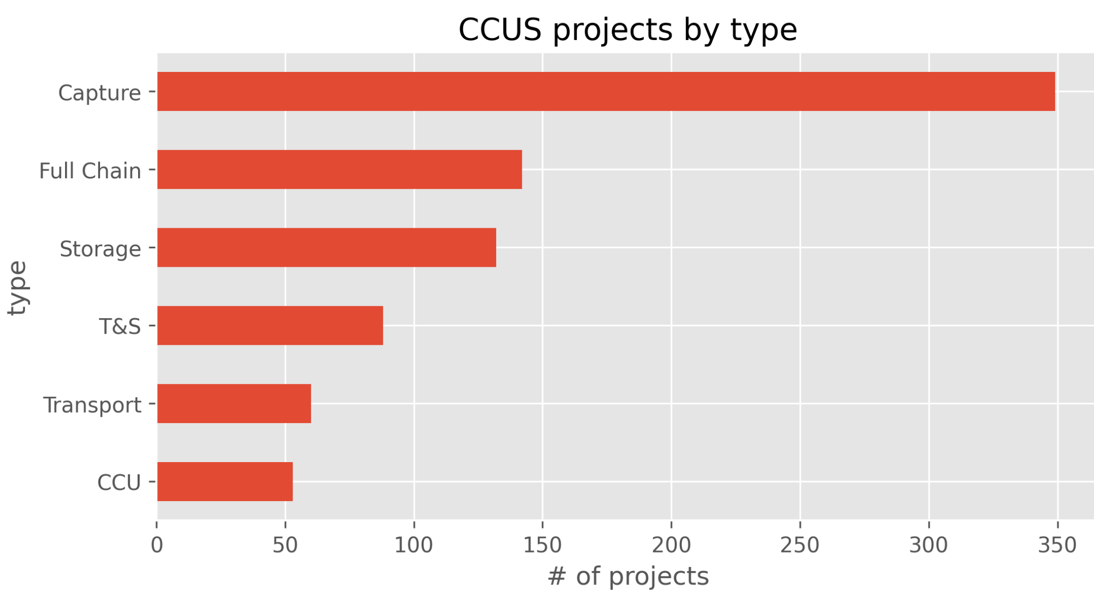
[27]:
```
df["country"].value_counts().sort_values(ascending=True).tail(20).plot.barh()
plt.xlabel("# of projects")
plt.title("CCUS projects by country (first 20)");
```



[28]:
```
df_rows_count = df.shape[0]
us_counts = (df["country"] == "United States").sum()
country_percentage = us_counts / df_rows_count
print(f"Projects based in the USA account for {country_percentage * 100:.2f}%␣
 ↪of total entries")
```

```
Projects based in the USA account for 34.95% of total entries
```

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



[30]:
```
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"Projects that capture carbon account for {type_percentage * 100:.2f}%␣
↪of total entries")
```

```
Projects that capture carbon account for 59.59% of total entries
```

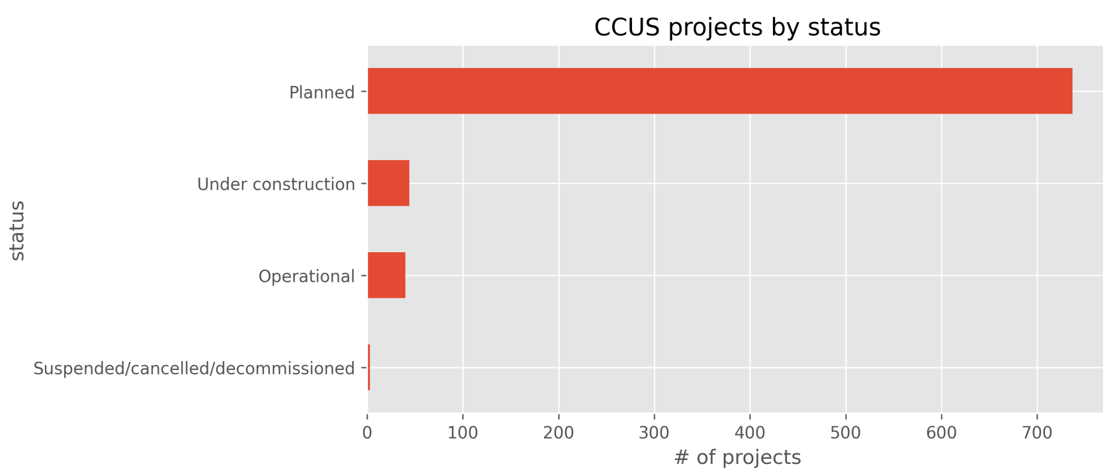
[31]:
```
df_rows_count = df.shape[0]
storage_counts = (
    (df["type"] == "Storage") | (df["type"] == "Full Chain") | (df["type"] ==␣
↪"T&S")
).sum()
type_percentage = storage_counts / df_rows_count
print(f"Storage projects account for {type_percentage * 100:.2f}% of total␣
↪entries")
```

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

[32]:
```
df_rows_count = df.shape[0]
transport_counts = ((df["type"] == "Transport") | (df["type"] == "Full Chain")␣
↪| (df["type"] == "T&S")).sum()
type_percentage = transport_counts / df_rows_count
print(f"Projects that transport carbon account for {type_percentage * 100:.2f}%␣
↪of total entries")
```

```
Projects that transport carbon account for 35.19% of total entries
```

[33]:
```
df["status"].value_counts().sort_values().plot.barh()
plt.xlabel("# of projects")
plt.title("CCUS projects by status");
```



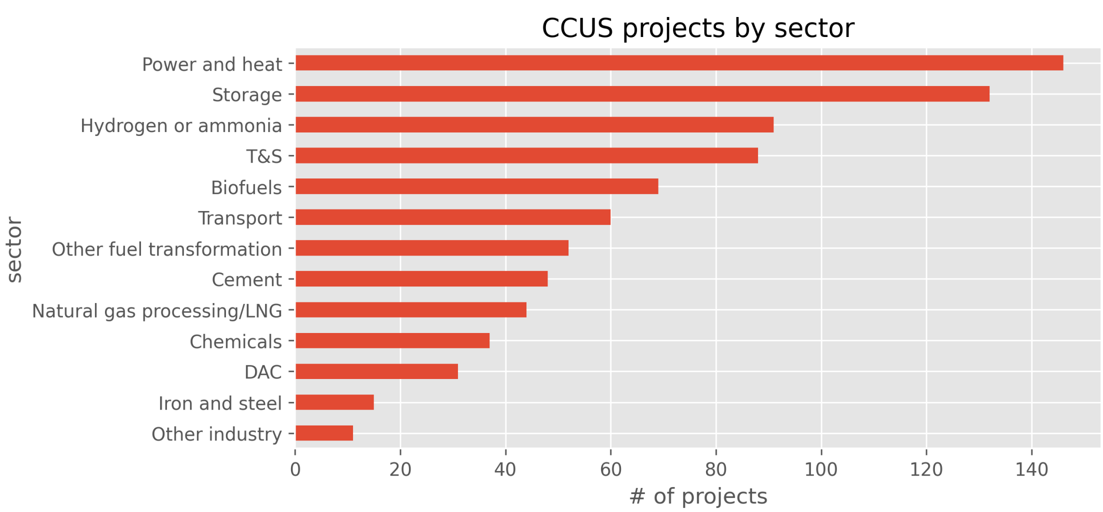
[34]:
```
df_rows_count = df.shape[0]
planned_counts = (df["status"] == "Planned").sum()
status_percentage = planned_counts / df_rows_count
print(f"Planned status accounts for {status_percentage * 100:.2f}% of total␣
↪entries")
```

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

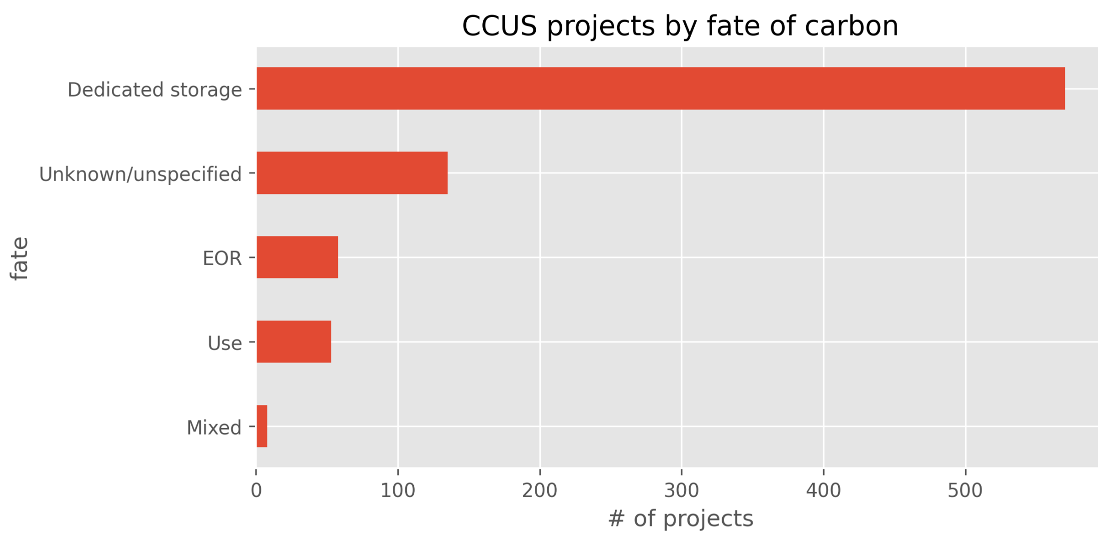
[35]:
```
df_rows_count = df.shape[0]
op_counts = (df["status"] == "Operational").sum()
status_percentage = op_counts / df_rows_count
print(
    f"Operational status accounts for {status_percentage * 100:.2f}% of total␣
↪entries"
)
```

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

[36]:
```
df["sector"].value_counts().sort_values(ascending=True).plot.barh()
plt.xlabel("# of projects")
plt.title("CCUS projects by sector");
```



[37]:
```
df["fate"].value_counts().sort_values().plot.barh()
plt.xlabel("# of projects")
plt.title("CCUS projects by fate of carbon");
```



[38]:
```
df_rows_count = df.shape[0]
fate_counts = (df["fate"] == "Dedicated storage").sum()
status_percentage = fate_counts / df_rows_count
print(f"Dedicated storage accounts for {status_percentage * 100:.2f}% of total␣
↪entries")
```

```
Dedicated 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 there is some diversity, most projects are concerned with capture (59.59%).
- 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

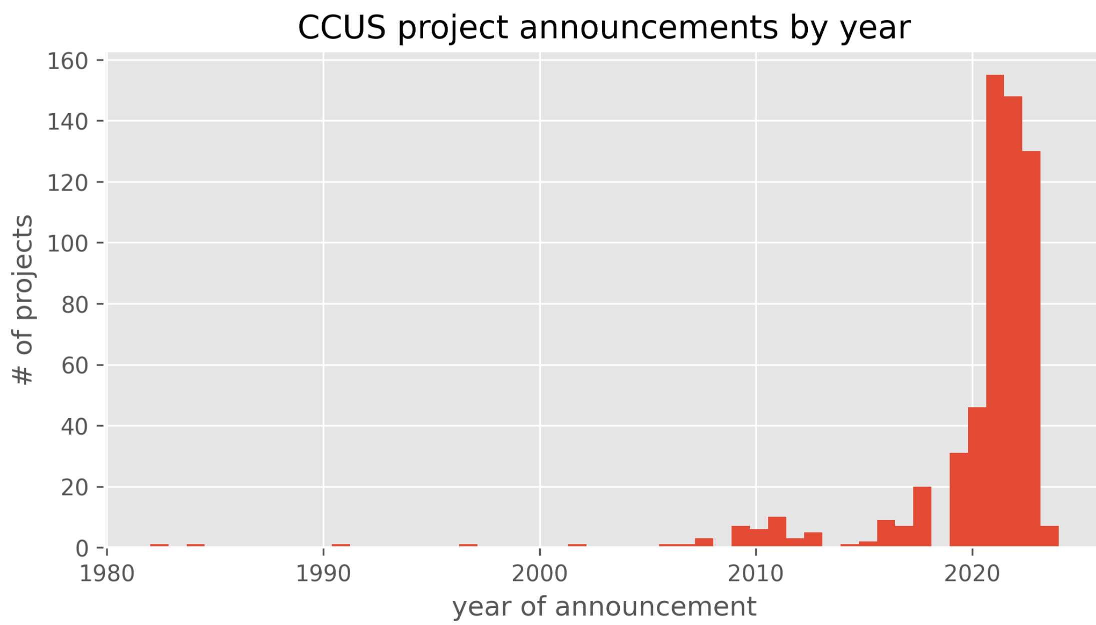
Here, we do some descriptive statistics of the numerical features:

- `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

For the reasons we previously specified, we use the `df_77` DataFrame for this.

[39]:
```
df_77["year"].hist(bins=50)
plt.ylabel("# of projects")
plt.xlabel("year of announcement")
plt.title("CCUS project announcements by year");
```

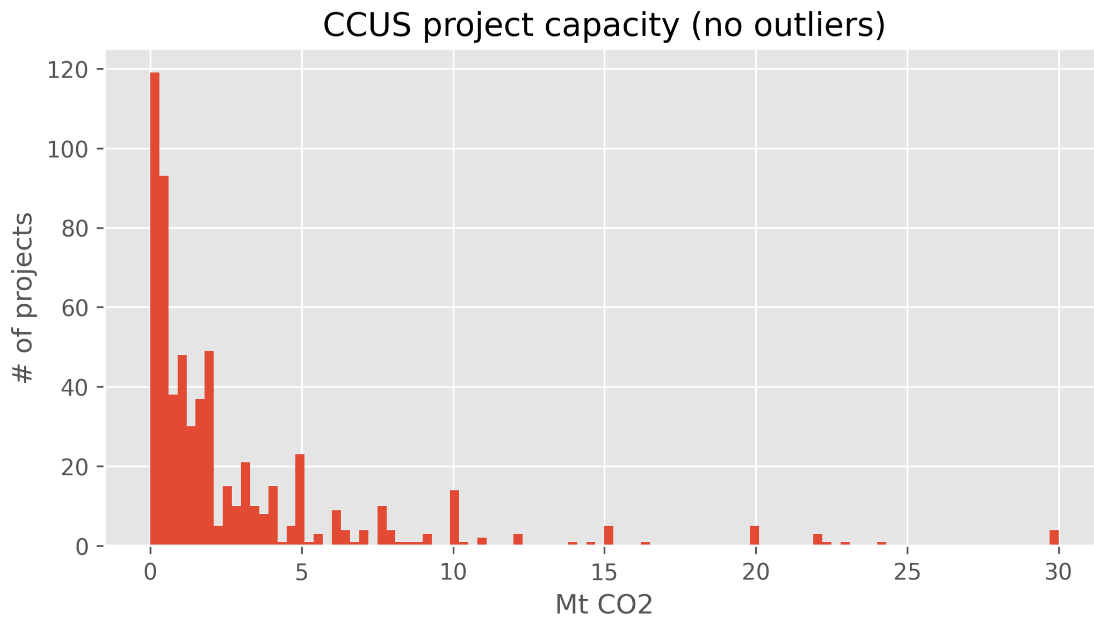


[40]:
```
year_2021 = df_77[df_77['year'] == 2021].shape[0]
year_2022 = df_77[df_77['year'] == 2022].shape[0]
year_2023 = df_77[df_77['year'] == 2023].shape[0]
```

[41]:
```
year_p = (year_2021 + year_2022 + year_2023) / df_77.shape[0]
print(f"{year_p * 100:.2f}% of projects announced in 2021-2023")
```

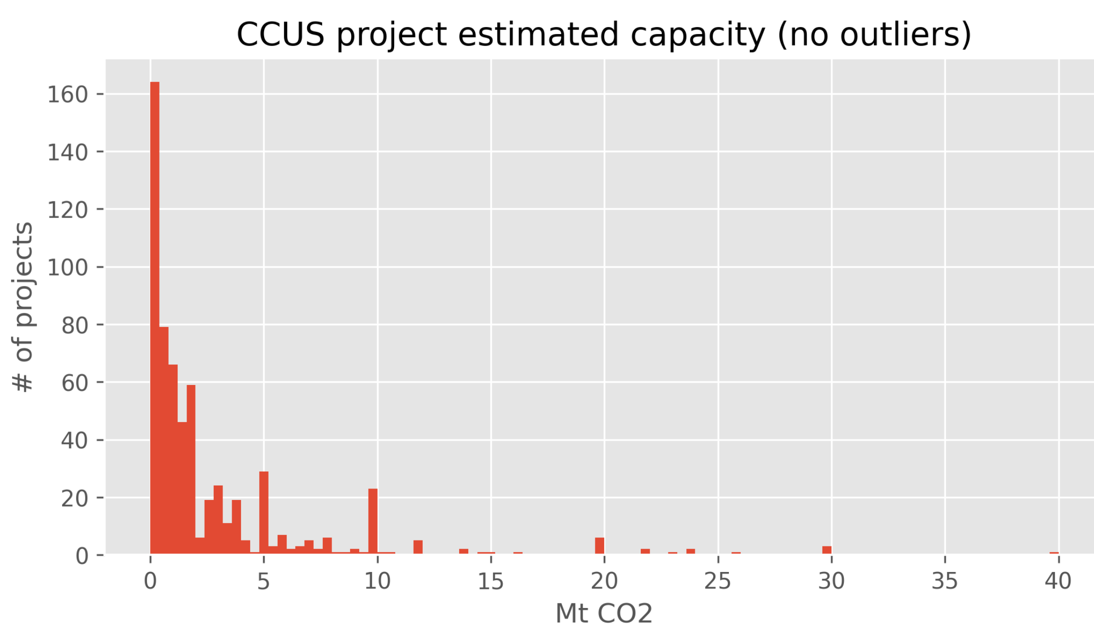
```
70.52% of projects announced in 2021-2023
```

[42]:
```
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)");
```



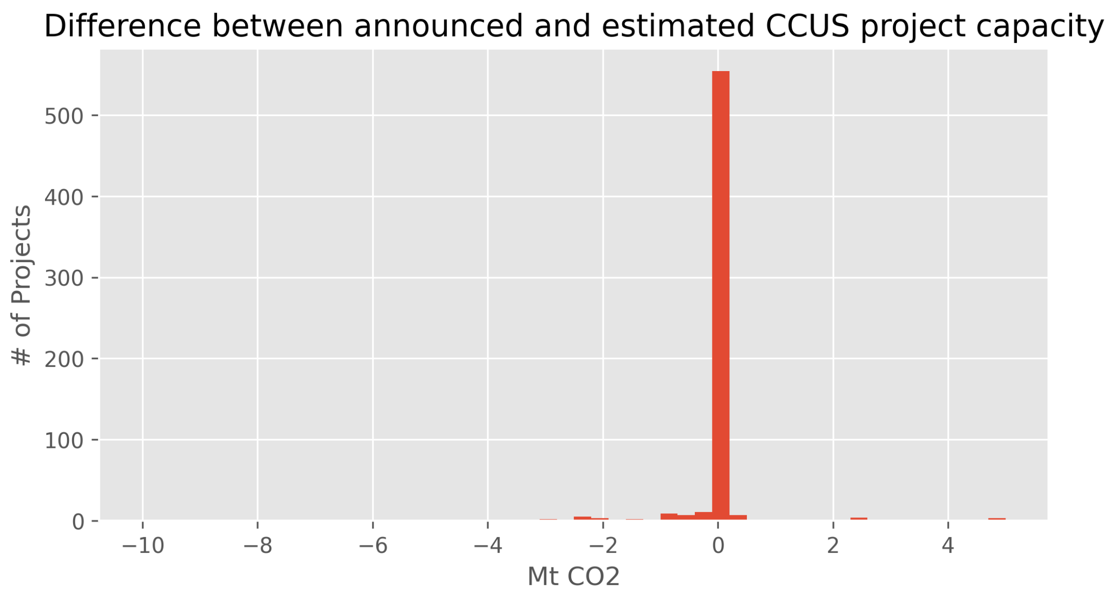
[43]:
```
df_77["capacity_est"].drop([635, 676]).hist(bins=100)
plt.xlabel("Mt CO2")
plt.ylabel("# of projects")
plt.title("CCUS project estimated capacity (no outliers)")
```

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



[44]:
```
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")
```

[44]:
```
Text(0.5, 1.0, 'Difference between announced and estimated CCUS project
capacity')
```



Since both capacity measures have 98% correlation, from now on we will treat them as the same.

[45]:
```
df_77[["capacity_ann", "capacity_est"]].drop([635, 676]).corr()
```

[45]:

	capacity_ann	capacity_est
capacity_ann	1.000000	0.987177
capacity_est	0.987177	1.000000

[46]:
```
less_5 = df_77[df_77["capacity_est"] < 35].shape[0]
print(f"Projects with less than 5   capacity: {less_5}")

less_5 = df_77[df_77["capacity_est"] < 5].shape[0]
print(f"Projects with less than 5   capacity: {less_5}")

less_2h = df_77[df_77["capacity_est"] < 2.5].shape[0]
print(f"Projects with less than 2.5 capacity: {less_2h}")

less_h = df_77[df_77["capacity_est"] < 0.5].shape[0]
```

```
print(f"Projects with less than 2   capacity: {less_h}")


print()
print(f"Most projects ({(less_2h / df_77.shape[0]) * 100:.2f}%) are in the 0-2.
↪5 range")
```

```
Projects with less than 5   capacity: 611
Projects with less than 5   capacity: 500
Projects with less than 2.5 capacity: 421
Projects with less than 2   capacity: 178

Most projects (68.57%) are in the 0-2.5 range
```

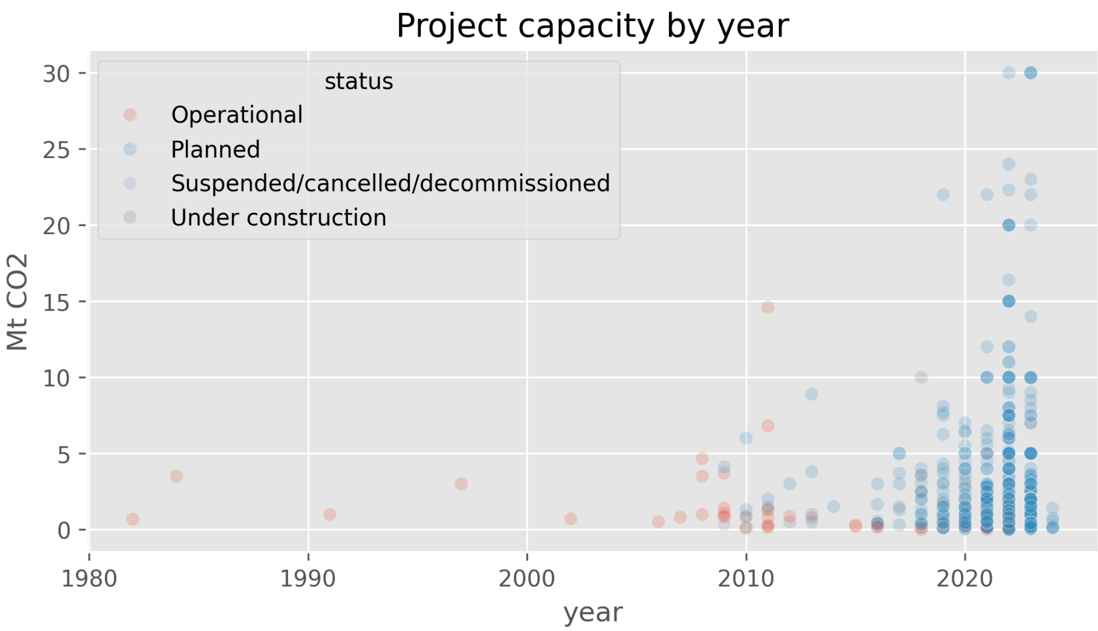
1.3.4 Insights

The data continues being mostly homogenous, with:

- **70%** of projects being announced in 2021-2023
- **70%** of projects having capacity between 0 and 2.5 Mt CO2

To illustrate this we can use this plot:

[47]:
```
sns.scatterplot(
    x="year",
    y="capacity_ann",
    data=df_77.drop([635, 676]),
    alpha=0.2,
    hue="status",
)
plt.ylabel("Mt CO2")
plt.title("Project capacity by year");
```



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. This points to the existence of a bug in the code.

[48]:
```
df_77[df_77["status"] == "Suspended/cancelled/decommissioned"]
```

[48]:
```
                                     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
```

[49]:
```
df_77[df_77["region"] == "Africa"]
```

[49]:
```
                        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.

[50]:
```python
df_77[df_77["capacity_ann"] > 100]
```

[50]:
```
                                          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
```

Most of the biggest (non-outlier) projects are from Europe.

They are still all transport (except Poseidon).

All of them are in the planning stage.

[51]:
```python
df_77[df_77["capacity_ann"] > 20].sort_values(by='capacity_ann',␣
↪ascending=False)
```

[51]:
```
                                          name   status         region  \
635  Port of Corpus Christi-Mississippi pipeline (TX)  Planned  North America
676                    Project WyoTCH pipeline (WY)  Planned  North America
319          Fluxys-Equinor Belgium-Norway Trunk Line  Planned         Europe
773                 The Bluestreak CO2 Joint Venture  Planned         Europe
794                  UK Poseidon CCS project phase 2  Planned         Europe
563                             North Sea CO2 corridor  Planned         Europe
```

```
299                   Equinor Smeaheia storage phase 2  Planned         Europe
659                    Project Crossroads (IN, IL, MI)  Planned  North America
338                       German carbon transport grid  Planned         Europe
249                              Delta Rhyne Corridor   Planned         Europe
53                        Aramis CCS transport phase 1  Planned         Europe
342                                   Gismarvik CO2 hub  Planned         Europe

                country     sector       type                 fate    year  \
635       United States  Transport  Transport  Unknown/unspecified  2023.0
676       United States  Transport  Transport  Unknown/unspecified  2023.0
319      Belgium-Norway  Transport  Transport    Dedicated storage  2022.0
773      United Kingdom        T&S        T&S    Dedicated storage  2023.0
794      United Kingdom    Storage    Storage    Dedicated storage  2023.0
563     Belgium-Germany  Transport  Transport    Dedicated storage  2023.0
299              Norway        T&S        T&S    Dedicated storage  2022.0
659       United States        T&S        T&S    Dedicated storage  2023.0
338             Germany  Transport  Transport    Dedicated storage  2022.0
249 Netherlands-Germany  Transport  Transport    Dedicated storage  2021.0
53          Netherlands  Transport  Transport    Dedicated storage  2019.0
342              Norway  Transport  Transport    Dedicated storage  2023.0

     capacity_ann  capacity_est  capacity_diff
635         250.0         250.0            0.0
676         120.0         120.0            0.0
319          30.0          40.0          -10.0
773          30.0          30.0            0.0
794          30.0          30.0            0.0
563          30.0          30.0            0.0
299          24.0          24.0            0.0
659          23.0          23.0            0.0
338          22.3          25.8           -3.5
249          22.0          22.0            0.0
53           22.0          22.0            0.0
342          22.0          24.0           -2.0
```

Here we see the older projects are all full chain. This might be explained by the fact that when they were built 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, and their sector is different from the biggest projects which are being planned. This is talked about in the commentary: "historically, oil and gas companies have been leaders in CCUS development". Most of them are also for EOR (enhanced oil recovery), which means they are not necessarily interested in reducing carbon emissions. They are also all still operational.

[52]:
```python
df_77[df_77["year"] < 2000]
```

[52]:
```
                                            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
```

1.3.6 Insights

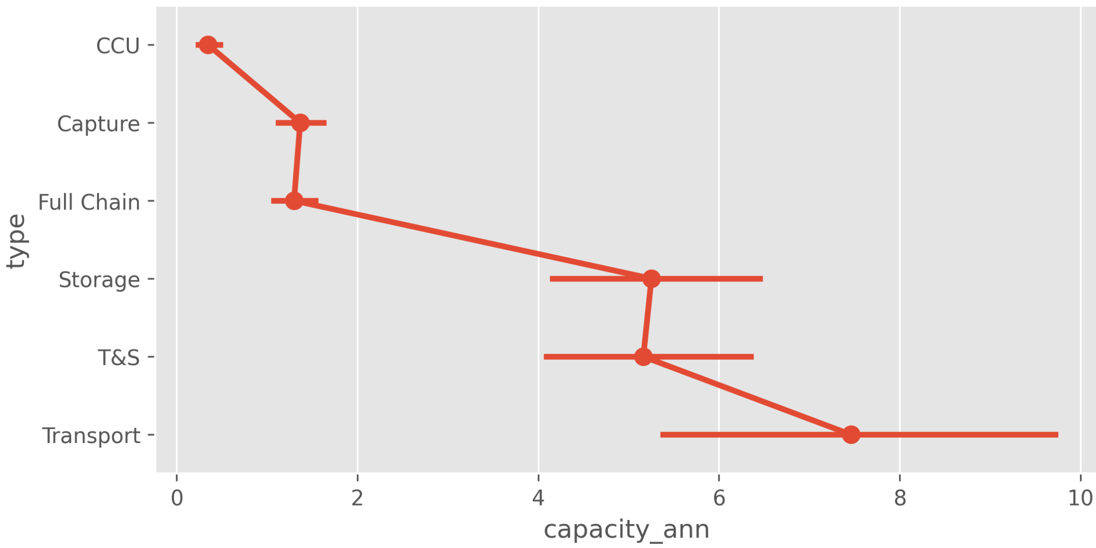
- Interesting projects might include
  - Bluestreak
  - Poseidon
  - Sleipner

1.4 Plotting and comparing features

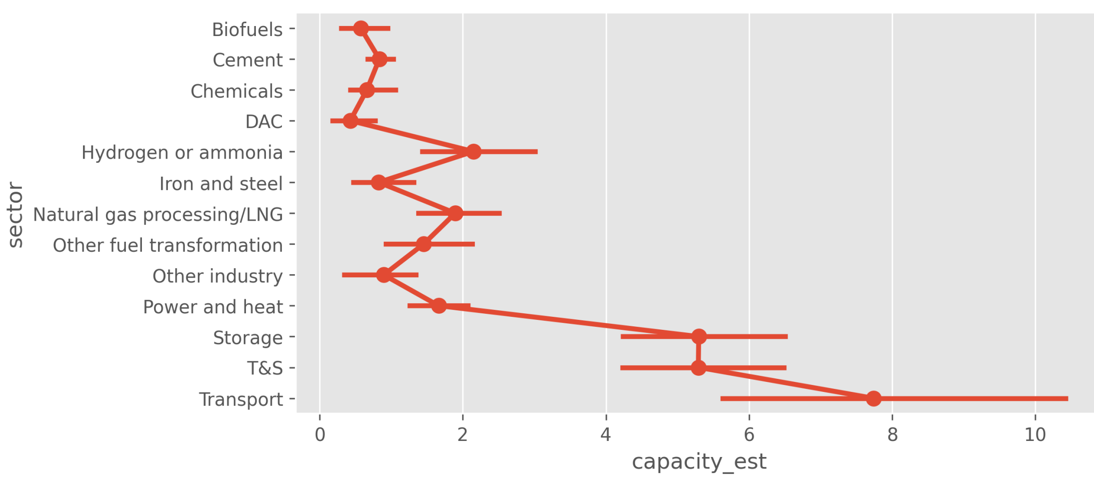
Here, we observe a few differences between categories: - transport projects have higher capacity - projects in Europe have higher capacity than projects in North America - projects being planned have higher capacity than projects in operation

[53]:
```
df_n = df_77.drop([635, 676])  # drop outliers
```

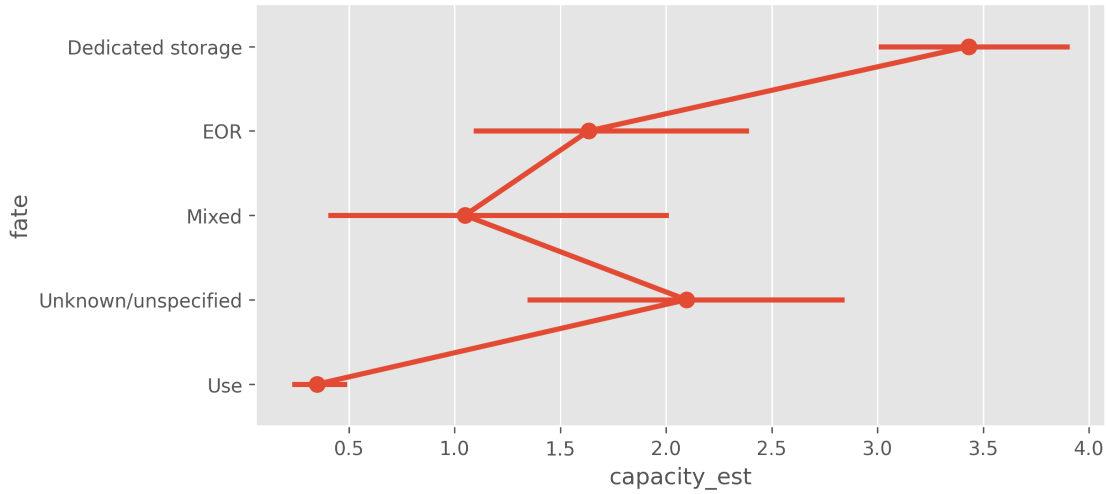
[54]:
```
sns.pointplot(x="capacity_ann", y="type", data=df_n);
```



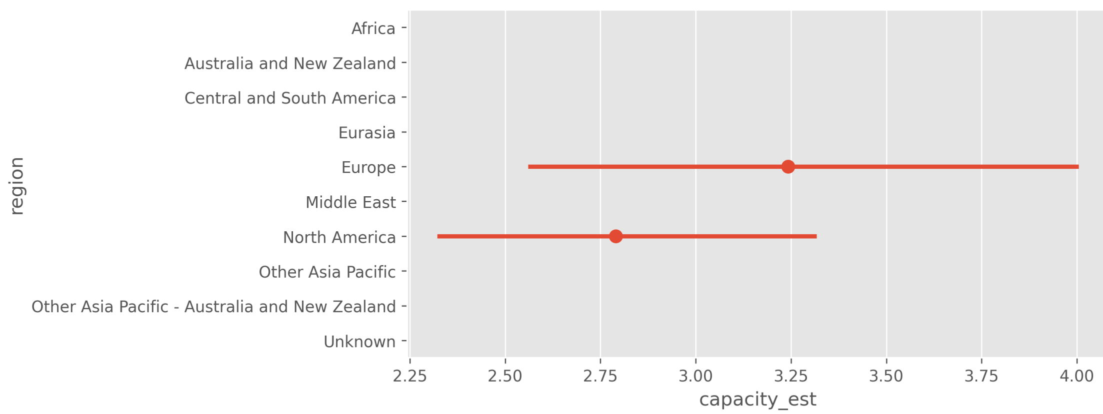
[55]:
```
sns.pointplot(x="capacity_est", y="sector", data=df_n);
```



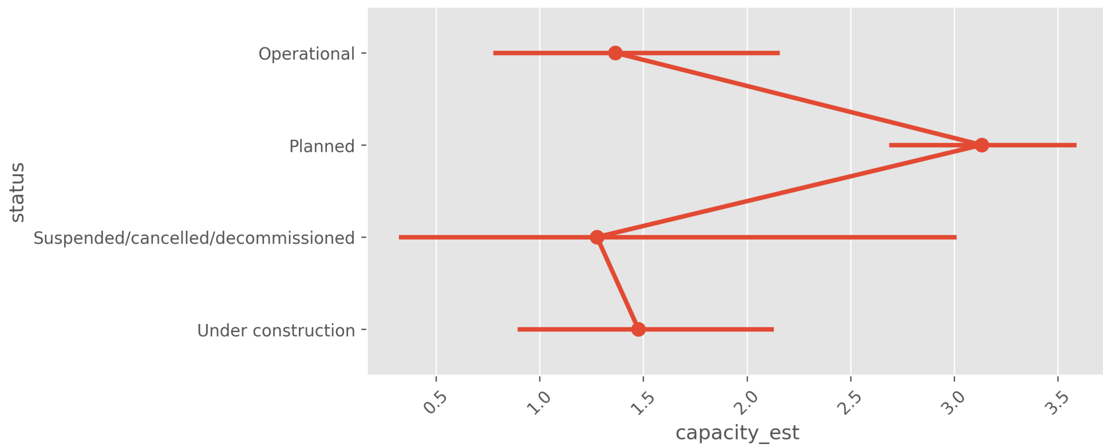
[56]:
```
sns.pointplot(x="capacity_est", y="fate", data=df_n);
```



[57]:
```
data = df_n[(df_n['region'] == "North America") | (df_n['region'] == "Europe")]
sns.pointplot(x="capacity_est", y="region", data=data);
```



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



[59]:
```
df_n["capacity_ann"][df_n["status"] == "Planned"].describe()
```

[59]:
```
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
```

[60]:
```
df_n["capacity_ann"][df_n["status"] != "Planned"].describe()
```

[60]:
```
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.

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.

We are comparing 86% (planning stage) to the other 14%, so this might be just random variation in the data. This is also not the point of the assignment. But, I mean, we are already here. Aren't you curious?

1.4.1 Null hypothesis significance test

H0: $\bar{x}$planned − $\bar{x}$other = 0

HA: $\bar{x}$planned − $\bar{x}$other   0

[61]:
```
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),
)
```

[62]:
```
cm.summary()
```

[62]:

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

[63]:
```
_, 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.

1.4.2 Just one more…

[64]:
```
st.CompareMeans(
    st.DescrStatsW(df_n["capacity_ann"][df_n["region"] == "Europe"]),
    st.DescrStatsW(df_n["capacity_ann"][df_n["region"] == "North America"]),
).summary()
```

[64]:

	coef	std err	t	P> |t|	[0.025	0.975]
subset #1	0.3470	0.416	0.835	0.404	-0.470	1.164

Looks like in this case (comparison between project capacity in Europe x US) the CI interval crosses zero and p is higher than 0.05. In this case, we do not reject the null hypothesis, which means that the difference in their capacity as observed in the plot is not statistically discernible.

1.5 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.
- **70%** of projects were announced in 2021-2023
- **70%** of projects have capacity between 0 and 2.5 Mt CO2
- 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.