The Patent Application Table (`TLS201_APPLN`)

Welcome to this look at one of the most fundamental tables in the PATSTAT database: the **Application Table**, designated as `TLS201_APPLN`. As we dive into this table, we will uncover what each field means in the context of the patent application process. This table serves as the foundation of patent data because it captures information about the patent applications themselves, which are the formal requests for patent protection.

What is a Patent Application?

A **patent application** is a legal document filed by an inventor (or the inventor's representative) to a patent office, requesting protection for a new invention. The application includes technical details about the invention and explains how it meets the requirements for a patent (such as novelty and inventiveness). The application is the **first step** in obtaining patent protection. However, the mere filing of an application does not guarantee that a patent will be granted—there are several steps in between.

Now, let's break down the key fields in this table and how they relate to the process of patenting. We need to initialize the PATSTAT client, and import the applications table first.

In [2]:
```
from epo.tipdata.patstat import PatstatClient

# Initialize the PATSTAT client
patstat = PatstatClient(env='PROD')

# Access ORM
db = patstat.orm()

# Importing the as models
from epo.tipdata.patstat.database.models import TLS201_APPLN
```

Key Fields in the `TLS201_APPLN` Table

APPLN_ID (Primary Key)

This is the **unique identifier** for each patent application in the PATSTAT database. Each application has a distinct `APPLN_ID`, which is used to reference and connect it to other tables and data points (like inventors, legal events, and publications).

In [2]:
```
q = db.query(
    TLS201_APPLN.appln_id
).limit(20000)

res = patstat.df(q)

res
```

Out[2]:

	appln_id
0	900802090
1	930345387
2	901105981
3	900875223
4	931261081
...	...
19995	4038729
19996	4038971
19997	4040645
19998	4040752
19999	4041274

20000 rows × 1 columns

PATSTAT contains dummy and artifical applications. These are identified by `appln_id` equal to zero or greater than 900 millions. For this reason, often in this notebook applications with ID greater than 900 millions will be filtered out. Indeed, considering outliers may result in misleading conclusions.

Having these applications is important to guarantee coherencein PATSTAT. Indeed, some prior applications are cited but this reference is not found in DOCDB.

APPLN_AUTH

The **application authority** indicates the **patent office** where the application was filed. Examples include "EP" for the European Patent Office, "US" for the United States Patent and Trademark Office, etc. This helps to identify the jurisdiction where protection is being sought.

In [3]:
```
q = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.appln_auth
).limit(20000)

res = patstat.df(q)

res
```

Out[3]:

	appln_id	appln_auth
0	900802090	CA
1	930345387	DE
2	901105981	CA
3	900875223	CA
4	931261081	JP
...	...	...
19995	4038729	CA
19996	4038971	CA
19997	4040645	CA
19998	4040752	CA
19999	4041274	CA

20000 rows × 2 columns

Grouping applications for each authority

Grouping applications by authority with ORM

Suppose that we are interested in getting the total number of applications filed in each authority. In order to do this we need an SQLAlchemy module called `func`. After importing the aforementioned module, we can use one of its functions, in our case the `count` function. We can rename the column by using the function `label`. Renaming is mandatory when using aggregating functions such as `count`.

In [3]:
```
# First of all, import the func module from sqlalchemy
from sqlalchemy import func

# Use the count function in the query and rename the column via t
he label command
group_q = db.query(
    func.count(TLS201_APPLN.appln_id).label('total_application
s'),
    TLS201_APPLN.appln_auth
).group_by(TLS201_APPLN.appln_auth)  # Here we use the group_by f
unction on the 'appln_auth' field

# Convert it in a dataframe
grouped_res = patstat.df(group_q)
grouped_res

# add bar chart with top 20 auth and explaining that we can quick
ly see the total number of auth looking at the index
```

Out[3]:

	total_applications	appln_auth
0	161204	SG
1	11367	TN
2	11	VA
3	9	SH
4	14337	EG
...	...	...
202	94376	CZ
203	63	MU
204	5	AW
205	3612030	CA
206	8076	IS

207 rows × 2 columns

Grouping applications by authority using Pandas

Since we are working with dataframes, we can execute the same operations by using Pandas functions, a very popular library to work with tabular data. It is already installed in TIP. In this case, what we need is `groupby` and `count` functions.

In [5]:
```
# Import pandas and rename it as pd (for sake of simplicity)
import pandas as pd

group_auth = res.groupby('appln_auth').count()
group_auth = group_auth.rename(columns={'appln_id': 'total_applic
ations'})
group_auth
```

Out[5]:

	total_applications
appln_auth	
AR	16
AT	477
AU	146
BE	422
BG	6
...	...
WO	11
XH	1
YU	12
ZA	43
ZM	4

66 rows × 1 columns

As we can notice, in this last output from Pandas we do not visualize the numeric index. This happens because the `groupby` function set the grouped field as index by default. However, we can easily change it by setting the `as_index` at 'False'.

In [6]:
```
group_auth = res.groupby('appln_auth', as_index=False).count()
group_auth = group_auth.rename(columns={'appln_id': 'total_applic
ations'})
group_auth
```

Out[6]:

	appln_auth	total_applications
0	AR	16
1	AT	477
2	AU	146
3	BE	422
4	BG	6
...	...	...
61	WO	11
62	XH	1
63	YU	12
64	ZA	43
65	ZM	4

66 rows × 2 columns

Why should we beinterested in having a numerical index? For sake of ease, we can keep the numerical index so that we can readily see the total number of authorities present in the database. Remember that the counting starts from 0. This means that there are 88 authorities.

Visualizing the applications for authority

A straightforward way to get the proportions between numbers is to visualize the data in charts. As an example, let's build a bar chart. To enable a better visualization, we select only the top 20 authorities.

As first step, let's use the `order_by` function to get the authorities in descending order by number of applications. Then we use the `limit` function to get the top 20 authorities.

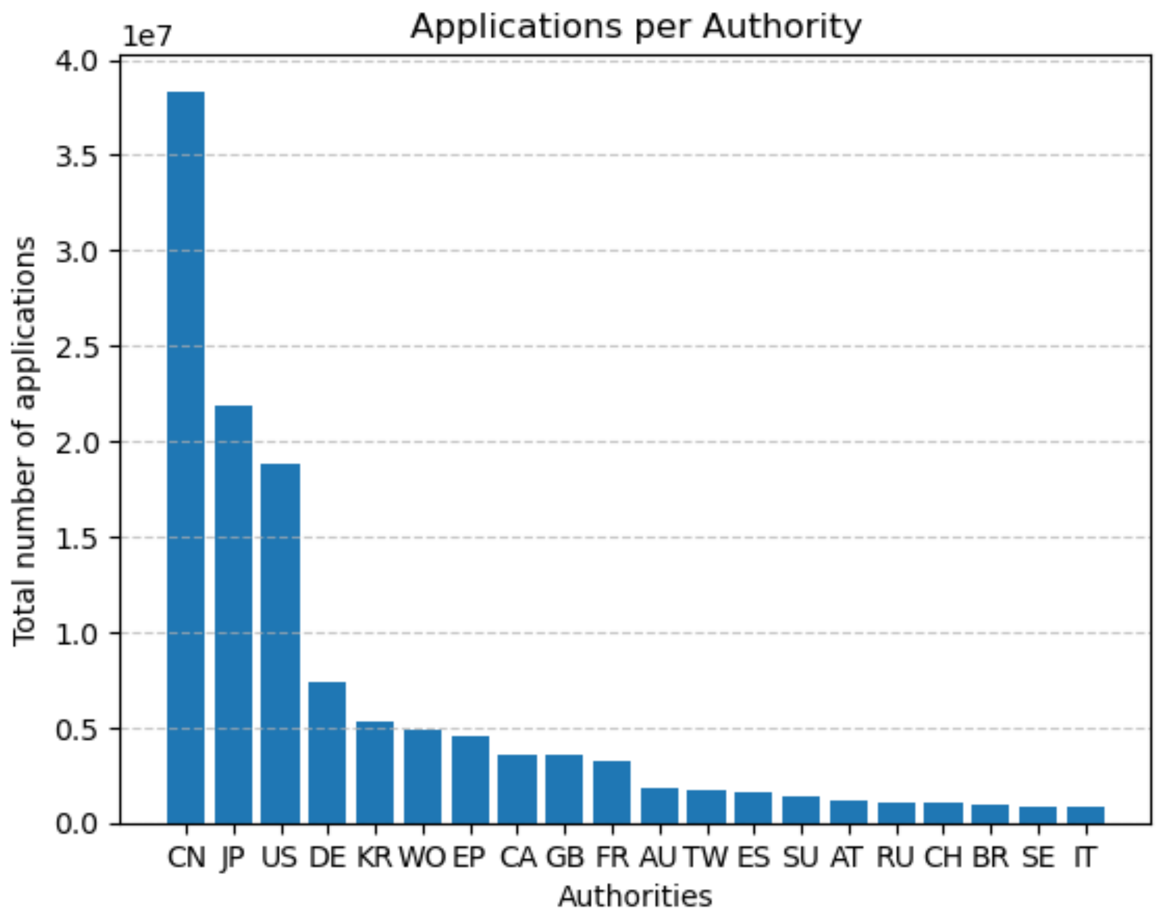
In [7]:
```
# Apply the order_by and the limit functions at the query previou
sly used

top_auth_q = db.query(
    func.count(TLS201_APPLN.appln_id).label('total_application
s'),
    TLS201_APPLN.appln_auth
).group_by(TLS201_APPLN.appln_auth).order_by(func.count(TLS201_AP
PLN.appln_id).desc()).limit(20)

top_auth_df = patstat.df(top_auth_q)
top_auth_df
```

Out[7]:

	total_applications	appln_auth
0	38349201	CN
1	21867386	JP
2	18865932	US
3	7396519	DE
4	5360107	KR
5	4829514	WO
6	4496597	EP
7	3612030	CA
8	3571821	GB
9	3221035	FR
10	1869740	AU
11	1732814	TW
12	1573611	ES
13	1406560	SU
14	1172505	AT
15	1080188	RU
16	1070481	CH
17	904070	BR
18	892618	SE
19	855524	IT

Now we can use this dataframe to create our bar plot. We do it by using the `matplotlib.pyplot` , a very popular library in Python that we find already installed in TIP. For details about plot generation, please refer to the official documentation here (https://matplotlib.org/stable/tutorials/index).

In [8]:
```
# Import matplotlib.pyplot renaming it as plt
import matplotlib.pyplot as plt

fig, ax = plt.subplots()

# Define the amounts to be displayed retriving them from the data frame created in the previous box
authorities = top_auth_df['appln_auth']
tot_applications = top_auth_df['total_applications']

ax.bar(authorities, tot_applications)

# Set axes labels and title of the plot
ax.set_xlabel('Authorities')
ax.set_ylabel('Total number of applications')
ax.set_title('Applications per Authority')

# Draw dot horizontal lines and plot the result
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



APPLN_NR

This is the actual **application number** assigned by the patent office. This number is often cited in official documentation and used to track the progress of the application. The application number is unique for each application authority.

In [9]:
```
# Use the query utilized at the beginning of this tutorial but se
lecting the application number instead of the application id
q = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.appln_nr,
    TLS201_APPLN.appln_auth
).limit(20000)

res_df = patstat.df(q)
res_df
```

Out[9]:

	appln_id	appln_nr	appln_auth
0	930214509	2620848	CN
1	930459598	201301629	ID
2	930377491	0012606240043	EM
3	930402303	88023260002	EM
4	930189467	64315	BG
...	...	...	...
19995	50387582	3775059D	US
19996	50387648	3775095D	US
19997	50418239	3792368D	US
19998	50420664	3793753D	US
19999	50421819	3794413D	US

20000 rows × 3 columns

Let's say that we are interested in the European applications only. To filter the result, we use the `filter` function.

In [10]:
```
q = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.appln_nr,
    TLS201_APPLN.appln_auth
).filter(
    TLS201_APPLN.appln_auth == 'EP',  # Filter the result selecti
ng only applications filed at the EPO
    TLS201_APPLN.appln_id <= 900000000
)

res_df = patstat.df(q)
res_df
```

Out[10]:

	appln_id	appln_nr	appln_auth
0	16438496	79301815	EP
1	16459639	80890139	EP
2	16460420	80900934	EP
3	16464653	81103062	EP
4	16470865	81109648	EP
...	...	...	...
4314601	570597719	22714968	EP
4314602	576503831	22738915	EP
4314603	577346431	22745738	EP
4314604	570695479	22305455	EP
4314605	596244276	23186597	EP

4314606 rows × 3 columns

As we can see, the only value under the column `appln_auth` is 'EP', indicating that the application numbers in this table refer to applications filed at the EPO, as we requested.

Uniqueness of the application number

After this mathematical theorem title, let's demonstrate that the application number is unique for each application authority. There are a few ways to do so. Here it is shown one of them. Specifically, the claim says that each indivual application, identified by its application ID, has a total of application number that amounts to 1 for each application authority. This is to say that if we `count` the number of distinct `appln_nr` for each application authority, i.e. we use a `group_by` on `appl_auth`, we find that each individual application has exactly one application number associated with each of the application authorities where it was filed.

In [11]:

```
q = db.query(
    TLS201_APPLN.appln_id,
    func.count(TLS201_APPLN.appln_nr).label('tot_appln_nr_associa
ted'),
    TLS201_APPLN.appln_auth
).filter(
    TLS201_APPLN.appln_auth == 'EP',
    TLS201_APPLN.appln_id <= 900000000
).group_by(TLS201_APPLN.appln_id,
           TLS201_APPLN.appln_auth)

res_df = patstat.df(q)
res_df
```

Out[11]:

	appln_id	tot_appln_nr_associated	appln_auth
0	16870888	1	EP
1	17137678	1	EP
2	17195711	1	EP
3	55841444	1	EP
4	57428504	1	EP
...	...	...	...
4314601	425115901	1	EP
4314602	470968733	1	EP
4314603	491736281	1	EP
4314604	520336437	1	EP
4314605	564219532	1	EP

4314606 rows × 3 columns

Try to remove the filter on the application authority to check that the claim holds in general for each application authority.

There are many rows and most of them are hidden so we have no guarantee that everything is correct in middle of the table too. However, this can be checked out quickly. We simply have to sum along the `tot_appln_nr_associated` and verify that the resulting number is equal to the last index plus 1. Another way to do so is to order by the attribute that we want to check. This second method will be used in the rest of this tutorial.

In [12]:
```
# Select the tot_appln_nr_associated column from the res_df dataf
rame and use the sum() Pandas function
check_num = res_df['tot_appln_nr_associated'].sum()
check_num
print("The obtained result is "+str(check_num)+", that is indeed
equal to "+str(check_num - 1)+" (last index number) + 1")
```

```
The obtained result is 4314606, that is indeed equal to 4314605 (
last index number) + 1
```

This proofs that the sentence claimed at the beginning of this section holds true.

Notice that the vice versa is not true.

In [4]:

```
qu = db.query(
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.appln_nr,
    func.count(TLS201_APPLN.appln_id).label('count_appln_nr')
).filter(
    TLS201_APPLN.appln_id <= 900000000
).group_by(
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.appln_nr
).having(
    func.count(TLS201_APPLN.appln_id) > 1
).order_by(
    func.count(TLS201_APPLN.appln_id)
)

duplicates = patstat.df(qu)
duplicates
```

Out[4]:

	appln_auth	appln_nr	count_appln_nr
0	US	25043D	2
1	CA	83915	2
2	ES	90254	2
3	ES	135619	2
4	DE	D0004728	2
...	...	...	...
6576354	WO	2010000001	71
6576355	WO	2009000001	73
6576356	WO	2016000001	73
6576357	WO	2012000001	76
6576358	WO	2015000001	77

6576359 rows × 3 columns

A clarification on this point. The high numbers of duplicates of `appln_nr` have 'WO' as `appln_auth`, meaning that they are PCT application filed in different national authorities (more details on this topic later on in this course). Nevertheless, this also can happen for some national authorities. However, there is no need to check the date to understand that they are very old applications. For example, the `appln_auth` 'DD' is East Germany.

APPLN_NR_EPODOC / APPLN_NR_ORIGINAL

These are alternative versions of the application number. The **EPODOC** format is standardized by the EPO and contains digits and letters, whereas the **original number** is the exact form in which it was submitted to the patent office.

So we have several numbers to identify applications in the database. Are them equivalent? The hope is that they are not, otherwise it means that the information contained in the database is redundant. Are all of them reliable in the same way? This is to say, can we use whatever standard we prefer to search in the database? Also, do all the applications have each of the different numbers associated to them? Let's perform an analysis to answer to these questions.

Only dummy and artificial applications do not have an appln_nr_epodoc

We start searching for applications without an EPODOC number, i.e. the ones having an empty string for the attribute `appln_nr_epodoc` . For all artificial applications the attribute `appln_nr_epodoc` will contain an empty string, hence we filter out such applications.

In [15]:
```
no_epodoc = db.query(
    TLS201_APPLN.appln_auth,
    func.count(TLS201_APPLN.appln_id).label('no_epodoc')  # Count the applications with no epodoc number
).filter(
    TLS201_APPLN.appln_nr_epodoc == '',  # Filter according to our search
    TLS201_APPLN.appln_id != 0,
    TLS201_APPLN.appln_id <= 900000000
).group_by(
    TLS201_APPLN.appln_auth
).order_by(
    func.count(TLS201_APPLN.appln_id).desc()
)

no_epodoc_df = patstat.df(no_epodoc)
print("There are "+str(len(no_epodoc_df))+" applications without EPODOC number")
```

```
There are 0 applications without EPODOC number
```

Let's see if the `appln_nr_epodoc` is unique for `appln_id` and `appln_auth` .

In [16]:
```
qu_epod = db.query(
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.appln_nr_epodoc,
    func.count(TLS201_APPLN.appln_id).label('count_nr_epodoc')
).filter(
    TLS201_APPLN.appln_id != 0,
    TLS201_APPLN.appln_id <= 900000000
).group_by(
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.appln_nr_epodoc
).having(
    func.count(TLS201_APPLN.appln_id) > 1
).order_by(
    func.count(TLS201_APPLN.appln_id)
)

unique = patstat.df(qu_epod)
unique
```

Out[16]:

	appln_auth	appln_nr_epodoc	count_nr_epodoc
0	GB	GB20190018778	2
1	AU	AU19950026801	2
2	IT	IT19840004840	2
3	AU	AU19940078401	2
4	AU	AU19880011801	2
...	...	...	...
8939	AU	AU20160000802	4
8940	AU	AU20120000902	4
8941	AU	AU20140000002	4
8942	AU	AU20150000402	4
8943	AU	AU20160000902	4

8944 rows × 3 columns

The number in `appln_nr_epodoc` is almost unique. For technical reasons, there are almost nine thousand applications with non-unique values in `appln_nr_epodoc`.

Some applications do not have an appln_nr_original

For all artificial applications the attribute `appln_nr_original` will contain an empty string. Therefore, let's just filter out artificial applications.

In [17]:
```
no_original = db.query(
    TLS201_APPLN.appln_auth,
    func.count(TLS201_APPLN.appln_id).label('no_original')
).filter(
    TLS201_APPLN.appln_nr_original == '',
    TLS201_APPLN.appln_id != 0,
    TLS201_APPLN.appln_id <= 900000000  # Filter out artificial a
pplications
).group_by(
    TLS201_APPLN.appln_auth
).order_by(
    func.count(TLS201_APPLN.appln_id).desc()
)

no_original_df = patstat.df(no_original)
no_original_df
```

Out[17]:

	appln_auth	no_original
0	DE	1339760
1	US	783425
2	FR	773915
3	JP	579685
4	BE	427191
...	...	...
94	EE	1
95	MO	1
96	ME	1
97	TN	1
98	MT	1

99 rows × 2 columns

The numbers observed are not negligible. However, what we really mind the most is the percentage of applications with number missing, over the total number of applications filed in each authority.

Size of the problem

In [18]:
```
# Start with computing the total number of applications filed in each authority
total = db.query(
    TLS201_APPLN.appln_auth,
    func.count(TLS201_APPLN.appln_id).label('total')
).group_by(
    TLS201_APPLN.appln_auth
).order_by(
    func.count(TLS201_APPLN.appln_id).desc()
)

# Create subqueries from the previous queries from which retrieve and put together the data needed
no_original_sub = no_original.subquery()
total_sub = total.subquery()

# Compute the percentages over the total number of applications for each application authority
overall = db.query(
    total_sub.c.appln_auth,
    (100 * no_original_sub.c.no_original / total_sub.c.total).label('no_original')
).filter(
    total_sub.c.appln_auth == no_original_sub.c.appln_auth
).order_by(
    (100 * no_original_sub.c.no_original / total_sub.c.total).desc()
)

overall_df = patstat.df(overall)
overall_df['no_original'] = overall_df['no_original'].astype(int)
overall_df
```

Out[18]:

	appln_auth	no_original
0	SM	99
1	DZ	91
2	TJ	90
3	GC	80
4	BE	65
...	...	...
94	ME	0
95	SA	0
96	EE	0
97	TN	0
98	EM	0

99 rows × 2 columns

It seems that there are many application authorities with a high percentage of applications without original number.

This does not mean that authorities with a smaller percentage (showed in the previous table) are easily accessible via these numbers. An authority can have a small percentage of applications with original number missing but a high number of applications overall, hence that small percentage may still result in a high number of application without original number.

NO APPLN_NR

Let's see if we encounter a similar problem with the application number seen in the previous section.

In [19]:
```
no_appln_nr = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.appln_auth,
    func.count(TLS201_APPLN.appln_id).label('no_appln_nr')
).filter(
    TLS201_APPLN.appln_nr == ''
).group_by(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.appln_auth
).order_by(
    func.count(TLS201_APPLN.appln_id).desc()
)

no_application_df = patstat.df(no_appln_nr)
no_application_df
```

Out[19]:

	appln_id	appln_auth	no_appln_nr
0	0	XX	1
1	930132237		1

Over the entire database, we count only 2 applications with application number missing. Furthermore, these are dummy applications, as can be seen looking at the application ID.

After the analysis in this section, we can conclude that the two most reliable number attribues are `appln_nr` and `appln_nr_epodoc` . The latter is also almost unique. In the Data Catalog there is an erroneous information, that is that `appln_nr_epodoc` is deprecated. This is actually not true. Therefore, we recommend to use `appln_nr_epodoc` to retrive applications from the database.

APPLN_KIND

The **kind code** describes the **type of application**. For example, whether it is a standard patent, a utility model, or another form of intellectual property protection. This is typically denoted by a letter (e.g., A1, B1) that specifies the stage or type of document.

In the **PATSTAT** database, specifically in the **TLS201_APPLN** table, the field **appln_kind** refers to the **application kind code**, which indicates the type of patent application. These codes are used to specify the legal nature of the application and its processing status. Each country or patent office uses a set of standardized codes to represent various kinds of applications. Here's an overview of the most common types of patent **application kinds**:

1. Utility Patent Applications:

- **A**: Standard utility patent applications are typically referred to by the code **A** in many jurisdictions. This is the most common form of application, intended to protect inventions like machines, processes, and compositions of matter.

2. Utility Models:

- **U**: This code is used for **utility models** in countries where they are offered. Utility models are similar to utility patents but usually have a shorter duration and less stringent patentability requirements. They are also referred to as "short-term" patents in some regions.

3. Divisional Applications:

- **D**: A **divisional application** is filed when the original application contains more than one invention, requiring the applicant to divide it into separate filings. Divisional applications retain the filing date of the parent application, which is critical for patent protection.

4. International (PCT) Applications:

- **P**: Under the **Patent Cooperation Treaty (PCT)**, an international application allows an inventor to seek protection in multiple countries by filing a single application. The kind code **P** designates such international filings.

5. Design Patents:

- **F**: Some jurisdictions use the **F** kind code to designate **design patents**. These patents protect the ornamental design of an article rather than its function.

6. Provisional Applications:

- **R**: Provisional applications (e.g., in the U.S.) allow an inventor to secure a filing date without submitting a full patent claim. These kinds of applications are often used to give the applicant more time to develop the invention while securing the priority date.

7. Continuation and Continuation-in-Part Applications:

- **C**: This code refers to **continuation applications**, which allow an inventor to modify or add new claims to an existing application while keeping the original filing date. **Continuation-in-Part (CIP)** applications allow for new matter to be added, unlike a regular continuation.

8. Supplementary Protection Certificates (SPCs):

- **S**: In certain jurisdictions, **S** refers to applications for **SPCs**, which extend the duration of a patent, typically for pharmaceutical and plant protection products, beyond the standard 20 years.

Why These Codes Matter:

Each of these application kinds reflects a specific legal strategy or procedural step in the patent application process. For example, a divisional application is filed to address situations where the original application claims more than one invention, while a provisional application is a cost-effective way to establish an early filing date.

Different patent offices may have variations in the kind codes they use, but they generally follow similar structures defined by **WIPO Standard ST.16**. This standard ensures consistency across countries, helping patent professionals and examiners understand the nature of an application across jurisdictions.

These kinds of codes play a crucial role in the lifecycle of a patent, determining how the application is processed, examined, and potentially granted.

Let's explore the `appln_kind` field. We start retrieving three columns: `appln_kind` , `appln_auth` and the count on `appln_id` . We also order the result by application authority.

In [20]:
```
appln_kinds = db.query(
    func.count(TLS201_APPLN.appln_id).label('tot_applications'),
    TLS201_APPLN.appln_kind,
    TLS201_APPLN.appln_auth
).group_by(
    TLS201_APPLN.appln_kind,
    TLS201_APPLN.appln_auth
).order_by(
    TLS201_APPLN.appln_auth
)

kinds_df = patstat.df(appln_kinds)
kinds_df
```

Out[20]:

	tot_applications	appln_kind	appln_auth
0	1	D2	
1	8	D2	AD
2	7	F	AE
3	1	U	AE
4	77	A	AE
...	...	...	...
907	3	D2	ZM
908	10	D2	ZW
909	1	F	ZW
910	2890	A	ZW
911	1	D	ZW

912 rows × 3 columns

It is clear that there are authorities where several kinds of applications were filed and other authorities with only one or a few kinds. Let's try to detail our analysis focusing on some particular aspects of the database.

For instance, we may be intersted in the number of different application kinds for each application authority. Notice that in order to get the distinct kinds of application we need the `distinct()` function, otherwise we would have a new count each time that the `appln_kind` field changes the value from row to row.

In [21]:
```
kinds_per_auth = db.query(
    func.count(TLS201_APPLN.appln_kind.distinct()).label('distinc
t_kinds'),  # Apply the distinct() function in order to avoid rep
eated counting
    TLS201_APPLN.appln_auth
).group_by(
    TLS201_APPLN.appln_auth
).order_by(func.count(TLS201_APPLN.appln_kind.distinct()).desc())
# Order by the number of distinct application kinds filed in each
authority in descending order so that we can see which are the ap
plication authorities with the highest number of distinct applica
tion kinds filed

kindsxauth_df = patstat.df(kinds_per_auth)
kindsxauth_df
```

Out[21]:

	distinct_kinds	appln_auth
0	27	DE
1	18	EP
2	17	US
3	16	CN
4	16	SU
...	...	...
202	1	NC
203	1	KW
204	1	GN
205	1	SH
206	1	JE

207 rows × 2 columns

To show that what we are doing is coherent and logical, we sum the values under the column `distinct_kinds`. What we should obtain is the same number of rows of the first table.

In [22]:
```
total = kindsxauth_df['distinct_kinds'].sum()
total
```

Out[22]: 912

The application authority with the highest number of distinct application kinds is United States. Let's see which kinds of application are filed in the US.

In [23]:
```
us_kinds = db.query(
    TLS201_APPLN.appln_kind.distinct().label('distinct_kinds'),
    TLS201_APPLN.appln_auth
).filter(TLS201_APPLN.appln_auth == 'US')  # Filter by appln_auth that must be 'US'

us_kinds_df = patstat.df(us_kinds)
us_kinds_df
```

Out[23]:

	distinct_kinds	appln_auth
0	p	US
1	P	US
2	Q	US
3	B2	US
4	A	US
5	F	US
6	D2	US
7	V	US
8	H	US
9	E	US
10	U	US
11	b	US
12	a	US
13	S	US
14	D	US
15	B	US
16	A1	US

Now we perform the same analysis for European applications.

In [24]:
```
eu_kinds = db.query(
    TLS201_APPLN.appln_kind.distinct().label('distinct_kinds'),
    TLS201_APPLN.appln_auth
).filter(TLS201_APPLN.appln_auth == 'EP')  # Filter by appln_auth that must be 'EP'

eu_kinds_df = patstat.df(eu_kinds)
eu_kinds_df
```

Out[24]:

	distinct_kinds	appln_auth
0	B6	EP
1	B1	EP
2	D	EP
3	A1	EP
4	T2	EP
5	U	EP
6	E	EP
7	a	EP
8	A4	EP
9	f	EP
10	P	EP
11	D2	EP
12	A	EP
13	B9	EP
14	B7	EP
15	F	EP
16	A3	EP
17	A2	EP

The EPO has two different kinds of application filed.

APPLN_FILING_DATE

This is one of the most important fields—the **filing date**. It represents the date on which the patent application was filed at the relevant patent office. This date establishes the patent's priority over other filings and is crucial for determining novelty.

Before start any kind of analysis, let's just take a glance of the format of the `appln_filing_date` field. We retrieve the `appln_filing_date` and `appln_auth` attributes. We should expect a huge number of rows.

In [25]:
```
dates = db.query(
    TLS201_APPLN.appln_filing_date,
    TLS201_APPLN.appln_auth
).order_by(
    TLS201_APPLN.appln_filing_date
).limit(500000)

dates_df = patstat.df(dates)
dates_df
```

Out[25]:

	appln_filing_date	appln_auth
0	1782-07-03	GB
1	1782-07-03	GB
2	1784-08-24	GB
3	1784-08-24	GB
4	1785-04-28	GB
...	...	...
499995	1902-03-05	CA
499996	1902-03-05	FR
499997	1902-03-05	AT
499998	1902-03-05	GB
499999	1902-03-05	FR

500000 rows × 2 columns

If we reverse the ordering of the filind date, we can see that there are many applications with year 9999. These are to be intended as missing date.

In [26]:
```
missing_dates = db.query(
    TLS201_APPLN.appln_filing_date,
    TLS201_APPLN.appln_auth
).order_by(
    TLS201_APPLN.appln_filing_date.desc()
).limit(500000)

missing_dates_df = patstat.df(missing_dates)
missing_dates_df
```

Out[26]:

	appln_filing_date	appln_auth
0	9999-12-31	CA
1	9999-12-31	TW
2	9999-12-31	BE
3	9999-12-31	BE
4	9999-12-31	KR
...	...	...
499995	9999-12-31	US
499996	9999-12-31	US
499997	9999-12-31	SE
499998	9999-12-31	JP
499999	9999-12-31	CA

500000 rows × 2 columns

Applications filed in the last quarter of 2022 for each application authority

As first exercise, let's see the ranking of the application authorities with the highest number of applications filed in the last quarter of 2022. Since ORM supports boolean operations between dates, we filter the data in order to get the applications filed in dates greater than or equal to 2022-10-01 and smaller than 2022-12-31. It is worth to remark that the words "greater" and "smaller" have a temporal meaning yet they help to build a bridge between the temporal concept and the boolean operations that we are going to use. We import `date` from `datetime` , already installed in TIP. This will enables us to define dates objects, i.e. the two bounding dates.

In [27]:
```
# Import date from datetime
from datetime import date

# Define the two bounding dates
start_date = date(2022,10,1)
end_date = date(2022,12,31)

filings = db.query(
    func.count(TLS201_APPLN.appln_id).label('num_of_application
s'),
    TLS201_APPLN.appln_auth
).filter(
    TLS201_APPLN.appln_filing_date >= start_date,
    TLS201_APPLN.appln_filing_date <= end_date  # Filter by filin
g date via the logical operators
).group_by(
    TLS201_APPLN.appln_auth
).order_by(func.count(TLS201_APPLN.appln_id).desc())

filings_df = patstat.df(filings)
filings_df
```

Out[27]:

	num_of_applications	appln_auth
0	1101376	CN
1	69890	US
2	60653	WO
3	24228	JP
4	16274	KR
...	...	...
68	1	ID
69	1	IR
70	1	DZ
71	1	PK
72	1	MN

73 rows × 2 columns

This shows a remarkable gap between the first authority, i.e. China, and the following ones.

The `appln_filing_date` attribute is helpful when we are interested in accessing the data referring to some specific quarter dates or range of dates. If we are interested in a particular year or a range of years instead, this can be easily accomplished by querying the `appln_filing_year` field and this nicely introduces the next section.

APPLN_FILING_YEAR

This field extracts the **year** from the filing date, making it easier to perform searches or statistical analyses based on the year of application.

Number of applications filed at the EPO from 2002 to 2022

We may be interested, for example, in the number of applications filed in EP each year from 2002 to 2022. In order to get this data we can use the same strategy as before, defining a starting and ending dates. This is not complicated yet it can be done in a more straightforward way, that is querying the years in which the applications were filed.

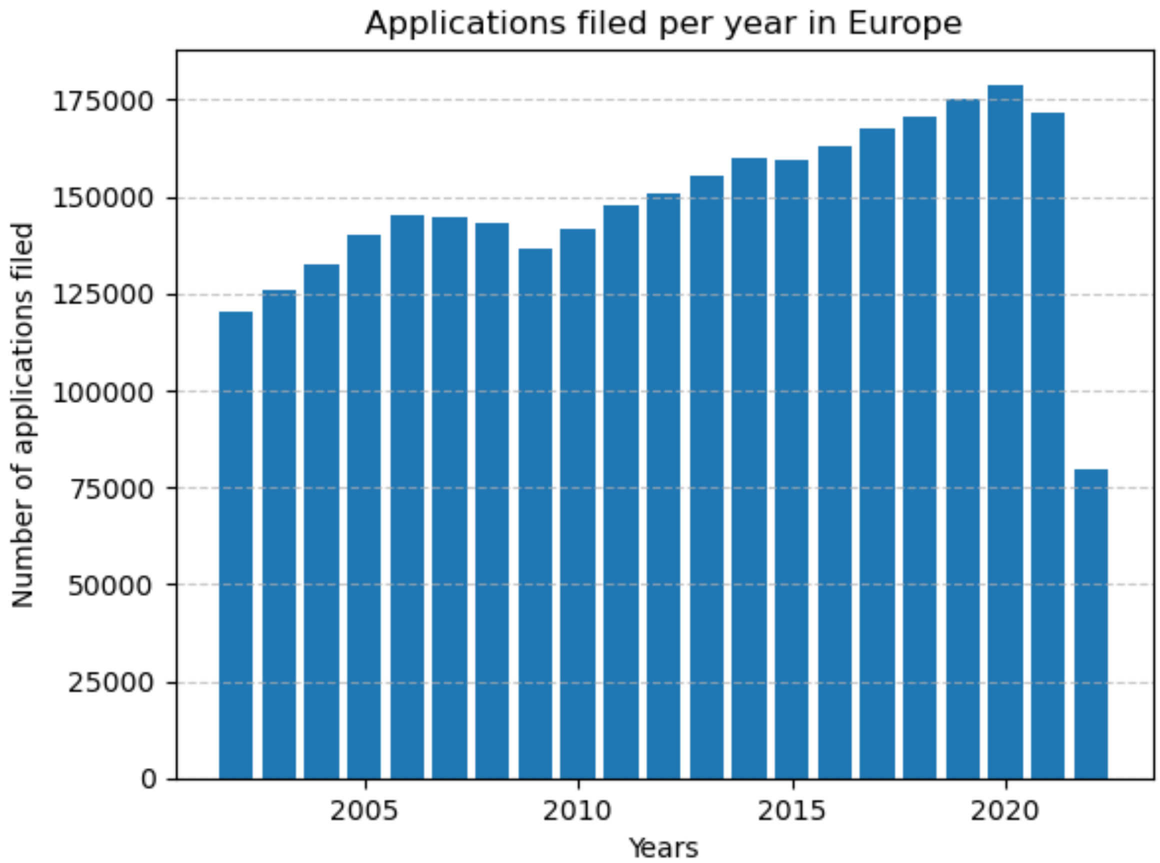
In [28]:
```
eu_filings_per_year = db.query(
    func.count(TLS201_APPLN.appln_id).label('num_of_application
s'),
    TLS201_APPLN.appln_filing_year
).filter(
    TLS201_APPLN.appln_filing_year >= 2002,  # Filtering the year
s
    TLS201_APPLN.appln_filing_year <= 2022,
    TLS201_APPLN.appln_auth == 'EP'  # Filtering EP applications
).group_by(TLS201_APPLN.appln_filing_year)

eu_filings_per_year_df = patstat.df(eu_filings_per_year)
eu_filings_per_year_df
```

Out[28]:

	num_of_applications	appln_filing_year
0	159470	2015
1	174958	2019
2	167590	2017
3	155471	2013
4	136565	2009
5	132300	2004
6	79813	2022
7	178875	2020
8	140035	2005
9	171378	2021
10	120429	2002
11	147597	2011
12	143290	2008
13	141872	2010
14	125684	2003
15	170473	2018
16	144806	2007
17	163066	2016
18	145337	2006
19	150576	2012
20	159978	2014

Let's visualize it in a bar plot to better grasp the trends of patents applications to the EPO in the last 20 years.

In [29]:
```
fig, ax = plt.subplots()

# Define the amounts to be displayed retriving them from the data
frame created in the previous box
years = eu_filings_per_year_df['appln_filing_year']
applications_filed = eu_filings_per_year_df['num_of_application
s']

ax.bar(years, applications_filed)

# Set axes labels and title of the plot
ax.set_xlabel('Years')
ax.set_ylabel('Number of applications filed')
ax.set_title('Applications filed per year in Europe')

plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



Monthly average number of applications filed at EPO from 2002 to 2022

Now let's move to a trickier exercise. Suppose that we are interested in knowing what is the month with the highest average number of applications filed in the period ranging from 2002 to 2022. Again, we limit the analysis to EP. In this example we see an application of a `subquery` , since we need it in order to carry out the analysis. To access the columns of the table resulting from the inner query we need to import `select` . Moreover, we need the `extract` function in order to select the desired month from the date. In short, the strategy is: counting the applications filed filtering by year and application authority (EP), grouping by month, and then computing the average, grouping again by month. The first part is the subquery. The need for this approach rises since it is not possible to compute aggregate functions of aggregate functions.

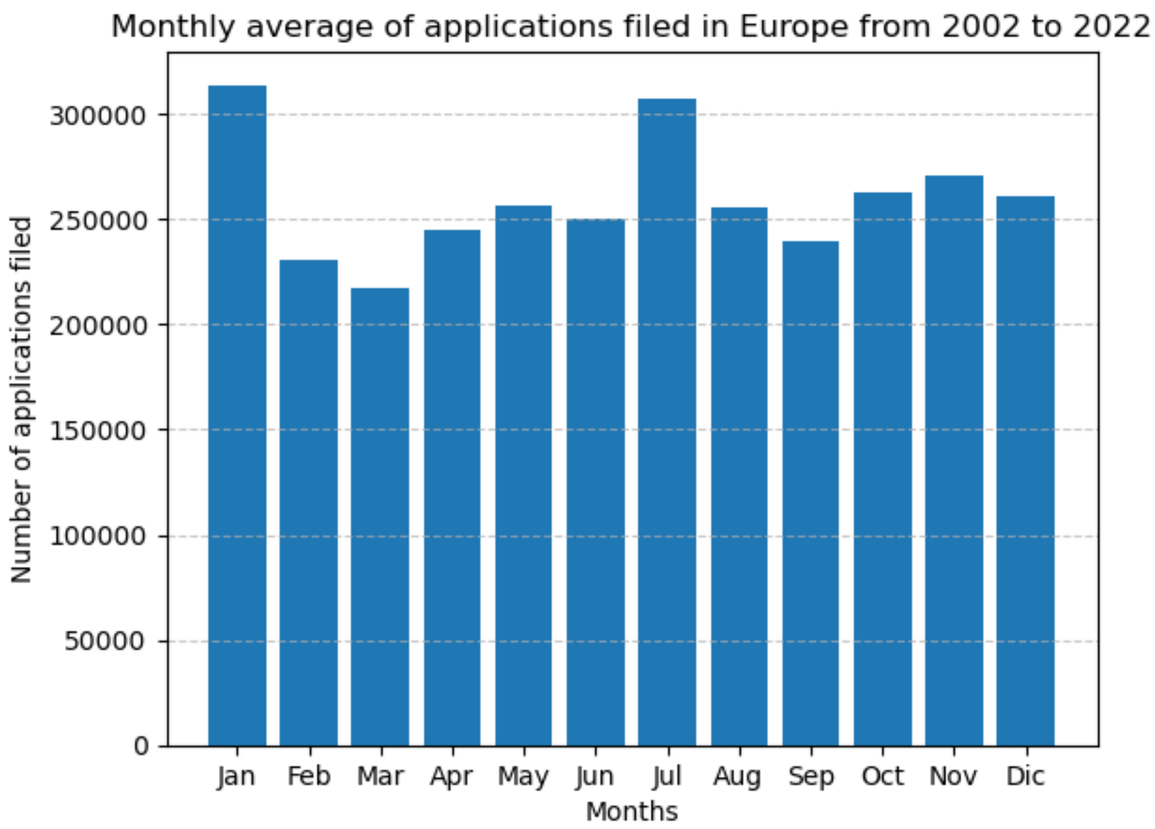
In [30]:
```
from sqlalchemy import extract, select

months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug',
'Sep', 'Oct', 'Nov', 'Dic']

# Inner query (subquery)
monthly_tot = db.query(
    func.count(TLS201_APPLN.appln_id).label('num_of_application
s'),
    extract('month', TLS201_APPLN.appln_filing_date).label('mont
h')
).filter(
    TLS201_APPLN.appln_filing_year >= 2002,
    TLS201_APPLN.appln_filing_year <= 2022,
    TLS201_APPLN.appln_auth == 'EP'
).group_by(
    extract('month', TLS201_APPLN.appln_filing_date)
).subquery()

# Outer query (notice that the command .c enables to access the c
olumns of the table resulting from the subquery)
monthly_avg = db.query(
    monthly_tot.c.month,
    func.avg(monthly_tot.c.num_of_applications).label('monthly av
erage')
).group_by(monthly_tot.c.month)

monthly_avg_df = patstat.df(monthly_avg)
monthly_avg_df['monthly average'] = monthly_avg_df['monthly avera
ge'].astype(int) # Set the type of the average values to integer
monthly_avg_df.index = months # Set the months in letters as inde
x just because it is nice
monthly_avg_df
```

Out[30]:

	month	monthly average
Jan	3	313681
Feb	8	230684
Mar	1	216916
Apr	4	244800
May	7	256477
Jun	5	250545
Jul	12	307418
Aug	11	255897
Sep	2	239351
Oct	9	262469
Nov	6	270468
Dic	10	260857

Below it is the visualization part.

In [31]:
```
fig, ax = plt.subplots()

# Define the amounts to be displayed retriving them from the data frame created in the previous box
months = monthly_avg_df.index
applications_filed = monthly_avg_df['monthly average'].values

ax.bar(months, applications_filed)

# Set axes labels and title of the plot
ax.set_xlabel('Months')
ax.set_ylabel('Number of applications filed')
ax.set_title('Monthly average of applications filed in Europe from 2002 to 2022')

plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



IPR_TYPE

The **intellectual property right type** defines what kind of protection the application is seeking, such as a patent, utility model, or design patent. Each type offers different scopes of protection.

To get familiar with the intellectual property right types, let's conduct a similar analysis to the one carried out for the application kind.

We start querying the ranking of the application authorities with the highest number of distinct types filed.

In [32]:
```
ipr_type = db.query(
    func.count(TLS201_APPLN.ipr_type.distinct()).label('num_of_ty
pes'),
    TLS201_APPLN.appln_auth
).group_by(
    TLS201_APPLN.appln_auth
).order_by(func.count(TLS201_APPLN.ipr_type.distinct()).desc())

ipr_type_df = patstat.df(ipr_type)
ipr_type_df
```

Out[32]:

	num_of_types	appln_auth
0	3	US
1	3	CH
2	3	MY
3	3	BY
4	3	SE
...	...	...
202	1	SZ
203	1	HT
204	1	CW
205	1	MU
206	1	CD

207 rows × 2 columns

Consider the top 2 authorities, i.e. Japan and Taiwan, and show the types of intellectual property right filed there.

In [33]:
```
jt_kinds = db.query(
    TLS201_APPLN.ipr_type.distinct().label('types'),
    TLS201_APPLN.appln_auth
).filter((TLS201_APPLN.appln_auth == 'JP') | (TLS201_APPLN.appln_auth == 'TW')  # Select the application authorities corresponding to JP or TW (using the | command)
).order_by(TLS201_APPLN.appln_auth)

jt_kinds_df = patstat.df(jt_kinds)
jt_kinds_df
```

Out[33]:

	types	appln_auth
0	PI	JP
1	UM	JP
2	DP	JP
3	UM	TW
4	DP	TW
5	PI	TW

We do the same for EP. We expect to get only one type of intellectual property right filed at the EPO, i.e. patent.

In [34]:
```
eu_types = db.query(
    TLS201_APPLN.ipr_type.distinct().label('types'),
    TLS201_APPLN.appln_auth
).filter(TLS201_APPLN.appln_auth == 'EP')

eu_types_df = patstat.df(eu_types)
eu_types_df
```

Out[34]:

	types	appln_auth
0	DP	EP
1	UM	EP
2	PI	EP

Only one type of intellectual property right filed at the EPO, that, indeed, is patent.

RECEIVING_OFFICE

This is the **office** that first received the application. In the case of international applications under the Patent Cooperation Treaty (PCT), this could be a national or regional office acting as the receiving office.

A simple analysis that we can perform is on which is the most frequent receiving office.

In [35]:
```
rec_off = db.query(
    TLS201_APPLN.receiving_office,
    func.count(TLS201_APPLN.appln_id).label('appln_filed')
).filter(
    TLS201_APPLN.appln_id <= 900000000
).group_by(
    TLS201_APPLN.receiving_office
)

rec_off_df = patstat.df(rec_off)
rec_off_df
```

Out[35]:

	receiving_office	appln_filed
0	ME	3
1	CZ	3229
2	SK	634
3	NL	26488
4	OM	49
...	...	...
108	HR	821
109	PT	1149
110	CU	270
111	MY	3343
112	GH	9

113 rows × 2 columns

The top receiving office is actually an empty string. This point will be covered later on in this section.

Out of curiosity, we can check how many times the EPO results as the receiving office.

In [36]:
```
ep_rec_off = db.query(
    TLS201_APPLN.receiving_office,
    func.count(TLS201_APPLN.appln_id).label('appln_filed')
).filter(
    TLS201_APPLN.receiving_office == 'EP',
    TLS201_APPLN.appln_id <= 900000000
).group_by(
    TLS201_APPLN.receiving_office
)

ep_rec_off_df = patstat.df(ep_rec_off)
ep_rec_off_df
```

Out[36]:

	receiving_office	appln_filed
0	EP	724705

To show the drastic difference between `appln_auth` and `receiving_office` we display the number of applications for which the two attribuites differ. As we noticed before, there are a lot of applications without a receiving office and these would count as a mismatch with the application authority. We prefer to ignore these cases in our analysis. Please notice that a missing receiving office is identified by a double empty space.

In [37]:
```
c = db.query(
    TLS201_APPLN.receiving_office,
    TLS201_APPLN.appln_auth
).filter(
    TLS201_APPLN.receiving_office != TLS201_APPLN.appln_auth,
    TLS201_APPLN.receiving_office != '  ',  # Ignore applications without a receiving office, devising double empty spaces
    TLS201_APPLN.appln_id < 900000000
).order_by(
    TLS201_APPLN.appln_auth
)

c_df = patstat.df(c)
c_df
```

Out[37]:

	receiving_office	appln_auth
0	US	WO
1	US	WO
2	US	WO
3	US	WO
4	CH	WO
...	...	...
4793042	CN	WO
4793043	CN	WO
4793044	CN	WO
4793045	CN	WO
4793046	DE	WO

4793047 rows × 2 columns

In the last query, the result is ordered by `appln_auth` to show that all the applications associated to a receiving office have the WIPO as application authority. Let's repeat this query but filtering the applications without a receiving office instead. This hopefully provides us with an explanation both for this result and that top number of filing observed in the first table of this section.

In [38]:
```
d = db.query(
    TLS201_APPLN.appln_auth
).filter(
    TLS201_APPLN.receiving_office != TLS201_APPLN.appln_auth,
    TLS201_APPLN.receiving_office == '  ',
    TLS201_APPLN.appln_id < 900000000
).order_by(
    TLS201_APPLN.appln_auth
).limit(500000)

d_df = patstat.df(d)
d_df
```

Out[38]:

	appln_auth
0	AM
1	AM
2	AM
3	AM
4	AM
...	...
499995	AT
499996	AT
499997	AT
499998	AT
499999	AT

500000 rows × 1 columns

Let's check if WIPO is present among the application authorities.

In [39]:
```
d_subquery = d.subquery()

w = db.query(
    d_subquery.c.appln_auth
).filter(
    d_subquery.c.appln_auth == 'WO'
)

w_df = patstat.df(w)
print("There are "+str(len(w_df))+" applications without receivin
g office and WIPO as application authority.")
```

```
There are 0 applications without receiving office and WIPO as app
lication authority.
```

This makes sense, since applications without the receiving office are not PCT applications.

INTERNAT_APPLN_ID

For international applications (those filed under the PCT), this field holds the **unique identifier** for PCT applications assigned by the PATSTAT team.

The default value 0 means this application has no earlier PCT application. If the value of `internat_appln_id` is greater than 0, then this application does have an earlier PCT application, whose `appln_id` equals the value of `internat_appln_id`.

Applications with a receiving office

Let's start checking what is the `internat_appln_id` for those applications with a receiving office. Therefore, we filter the application with the `receiving_office` different from the double empty space. We also check the corresponding `appln_auth`.

For computational reasons, we work in 'TEST' in this section.

In [40]:
```
patstat = PatstatClient(env='TEST')

db = patstat.orm()
```

In [41]:
```
internat = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.internat_appln_id,
    TLS201_APPLN.receiving_office,
    TLS201_APPLN.appln_auth
).filter(
    TLS201_APPLN.receiving_office != '  ',
    TLS201_APPLN.appln_id < 900000000
).order_by(
    TLS201_APPLN.internat_appln_id
)

internat_df = patstat.df(internat)
internat_df
```

Out[41]:

	appln_id	internat_appln_id	receiving_office	appln_auth
0	973495	0	AT	WO
1	41851262	0	NL	WO
2	43437960	0	SE	WO
3	46895543	0	US	WO
4	46913024	0	US	WO
...	...	...	...	...
20932	596524674	0	US	WO
20933	597159619	0	US	WO
20934	597707559	0	US	WO
20935	576699090	0	ZA	WO
20936	604330031	0	CN	WO

20937 rows × 4 columns

All of these applications are assigned with an international ID equal to 0 and the corresponding application authority is always the WIPO.

Applications without a receiving office

Let's check the opposite case: applications without a receiving office.

In [42]:
```
internat0 = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.internat_appln_id,
    TLS201_APPLN.appln_auth
).filter(
    TLS201_APPLN.receiving_office == '  ',
    TLS201_APPLN.appln_id < 900000000
).order_by(
    TLS201_APPLN.internat_appln_id
)

internat0_df = patstat.df(internat0)
internat0_df
```

Out[42]:

	appln_id	internat_appln_id	appln_auth
0	23307078	0	GB
1	23307812	0	GB
2	47805262	0	US
3	3150828	0	BE
4	3084616	0	BE
...	...	...	...
302098	267646284	909166996	US
302099	334495749	909167813	US
302100	445918801	909168527	US
302101	325209666	909168667	US
302102	566460456	909170881	US

302103 rows × 3 columns

International application ID equal to zero

We obtain both international IDs equal to 0 than greater than 0. Let's separate the two cases. We start querying applications with international ID equal to 0.

In [43]:
```
internat00 = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.internat_appln_id,
    TLS201_APPLN.appln_auth
).filter(
    TLS201_APPLN.internat_appln_id == 0,
    TLS201_APPLN.receiving_office == '  ',
    TLS201_APPLN.appln_id < 900000000
)

internat00_df = patstat.df(internat00)
internat00_df
```

Out[43]:

	appln_id	internat_appln_id	appln_auth
0	23307078	0	GB
1	23307812	0	GB
2	47805262	0	US
3	3150828	0	BE
4	3084616	0	BE
...	...	...	...
254783	604951886	0	KR
254784	604951821	0	KR
254785	605752605	0	KR
254786	605759471	0	KR
254787	602886417	0	KR

254788 rows × 3 columns

We check if the WIPO is present among these application authorities.

In [44]:
```
sub = internat00.subquery()

res_sub = db.query(
    sub.c.appln_id,
    sub.c.internat_appln_id,
    sub.c.appln_auth
).filter(
    sub.c.appln_auth == 'WO'
)

res_sub_df = patstat.df(res_sub)
print("WO is present "+str(len(res_sub_df))+" times.")
```

```
WO is present 0 times.
```

We can also see that there are applications filed directly to the EPO with no previous PCT applications.

In [45]:
```
res_sub_ep = db.query(
    sub.c.appln_id,
    sub.c.internat_appln_id,
    sub.c.appln_auth
).filter(
    sub.c.appln_auth == 'EP'
)

res_sub_ep_df = patstat.df(res_sub_ep)
res_sub_ep_df
```

Out[45]:

	appln_id	internat_appln_id	appln_auth
0	16427397	0	EP
1	16427726	0	EP
2	16430987	0	EP
3	16431185	0	EP
4	16431627	0	EP
...	...	...	...
9889	596773199	0	EP
9890	597130083	0	EP
9891	597167063	0	EP
9892	589782537	0	EP
9893	590989842	0	EP

9894 rows × 3 columns

Positive international application ID

Now we want to see what is the application authority and the receiving office for those applications with an international ID greater than 0. We expect to not find any receiving office, since a positive international ID means that the application does have a previous PCT application. We also select the application filing date, since it will be useful later on in this section.

In [46]:
```
pos_internat_id = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.internat_appln_id,
    TLS201_APPLN.receiving_office,
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.appln_filing_date
).filter(
    TLS201_APPLN.internat_appln_id != 0,
    TLS201_APPLN.appln_id < 900000000
).order_by(
    TLS201_APPLN.receiving_office
)

pos_internat_id_df = patstat.df(pos_internat_id)
pos_internat_id_df
```

Out[46]:

	appln_id	internat_appln_id	receiving_office	appln_auth	appln_filing_date
0	50522653	46932129		US	1982-03-05
1	10530370	46932399		DE	1980-10-01
2	49371760	47006561		US	1981-08-17
3	53887677	47006780		US	1986-05-05
4	2425098	20140159		AU	1982-10-15
...	...	...	...	...	...
47310	578690114	601604469		CN	2022-05-05
47311	601176698	604358660		CN	2022-06-30
47312	596534034	595613605		KR	2022-08-24
47313	602879973	602333283		KR	2022-09-26
47314	599761269	598710815		KR	2023-02-28

47315 rows × 5 columns

Ordering by `receiving_office` we are sure that there are not applications with a positive international ID assigned with a receiving office, according to the model adopted in PATSTAT.

In [47]:
```
pos_internat_id_sub = pos_internat_id.subquery()

wo = db.query(
    pos_internat_id_sub.c.appln_id,
    pos_internat_id_sub.c.internat_appln_id,
    pos_internat_id_sub.c.appln_auth
).filter(
    pos_internat_id_sub.c.appln_auth == 'WO'
)

wo_df = patstat.df(wo)
print("The number of applications with positive international ID that have the WIPO as application authority is "+str(len(wo_df)))
```

```
The number of applications with positive international ID that ha
ve the WIPO as application authority is 0
```

To prove that our reasoning is correct and the structure of the database is coherent, we search for `appln_id` s in the original table (`TLS201_APPLN`) that are equal to the international IDs that we have just retrived. To do so, we use again the `pos_internat_id` table previously generated as subquery. Moreover, we show the filing dates corresponding to both the first application, linked to the `appln_id` , and the later application, linked to the `internat_appln_id` . We expect these two dates to differ in some cases.

In [48]:
```
# Retrive all the data from table TLS201_APPLN except for interna
t_appln_id, retrived from pos_internat_id
ret = db.query(
    TLS201_APPLN.appln_id,
    pos_internat_id_sub.c.internat_appln_id,
    TLS201_APPLN.receiving_office,
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.appln_filing_date.label('application filing dat
e'),  #  Filing date of the application itself
    pos_internat_id_sub.c.appln_filing_date.label('international
filing date')  # Filing date of the international application
).filter(
    TLS201_APPLN.appln_id == pos_internat_id_sub.c.internat_appln
_id  # Filter searching for appln_id and internat_appln_id matche
s between the two tables
)

ret_df = patstat.df(ret)
ret_df
```

Out[48]:

	appln_id	internat_appln_id	receiving_office	appln_auth	application filing date	international filing date
0	46969238	46969238	US	WO	1982-07-19	1982-07-19
1	47043977	47043977	US	WO	1986-01-21	1986-01-21
2	47045187	47045187	US	WO	1986-05-19	1988-01-15
3	15654829	15654829	EP	WO	1989-12-12	1989-12-12
4	15656883	15656883	EP	WO	1990-11-30	1992-07-09
...	...	...	...	...	...	...
33086	588076755	588076755	EP	WO	2023-02-21	2023-02-21
33087	573723870	573723870	IB	WO	2022-05-22	2022-05-22
33088	596382310	596382310	JP	WO	2022-01-20	2022-01-20
33089	597223092	597223092	JP	WO	2022-02-10	2022-02-10
33090	594927647	594927647	US	WO	2023-06-07	2023-06-07

33091 rows × 6 columns

Now we can if the opposite can happen, that is finding `appln_id` already associated to a positive `internat_appln_id` that are equal to other international ID. This should not be the case, since positive international ID are associated only to application ID corresponding to first international applications.

In [49]:
```
rev = db.query(
    pos_internat_id_sub.c.appln_id,
    TLS201_APPLN.internat_appln_id,
    pos_internat_id_sub.c.receiving_office,
    pos_internat_id_sub.c.appln_auth
).filter(
    TLS201_APPLN.internat_appln_id == pos_internat_id_sub.c.appln
_id
)

rev_df = patstat.df(rev)
print("The number of applications that match the condition requir
ed is "+str(len(rev_df)))
```

```
The number of applications that match the condition required is 0
```

INT_PHASE, REG_PHASE, NAT_PHASE

These fields track the **status of the application** in various phases:

- **INT_PHASE**: International phase (for PCT applications, the stage before entering national phases).
- **REG_PHASE**: Regional phase (when an application enters a regional office, like the EPO).
- **NAT_PHASE**: National phase (when a PCT application enters individual countries for patent examination).

To have an overview of these attributes, we can select a specific DOCDB family ID and show some related fields. In the example below, we have applications related to the DOCDB family with ID equal to 23307812. Some of its applications have `internat_appln_id` greater than 0 and blank `receiving_office`, meaning that they are international applications. Indeed, the `int_phase` attribute is set at 'Y'. Other applications have `internat_appln_id` equal to 0. In one case we see that `receiving_office` is 'US' and `appln_auth` is 'WO', meaning that it is an international application and `int_phase` is 'Y' indeed. Notice that `reg_phase` is 'N' and it could not be otherwise, since the receiving office is 'US'. For two other applications, `receiving_office` is blank and `appln_auth` is not 'WO' and `int_phase` is 'N' indeed.

In [3]:
```
# Go back to PROD
patstat = PatstatClient(env='PROD')

db = patstat.orm()
```

In [7]:
```
fam_story = db.query(
    TLS201_APPLN.appln_nr,
    TLS201_APPLN.internat_appln_id,
    TLS201_APPLN.docdb_family_id,
    TLS201_APPLN.receiving_office,
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.int_phase,
    TLS201_APPLN.reg_phase,
    TLS201_APPLN.nat_phase
).filter(
    TLS201_APPLN.appln_id < 900000000,
    TLS201_APPLN.docdb_family_id == 23307812
)

fam_story_df = patstat.df(fam_story)
fam_story_df
```

Out[7]:

	appln_nr	internat_appln_id	docdb_family_id	receiving_office	appln_auth	int_phase
0	0009744	0	23307812	US	WO	Y
1	2001505032	45574554	23307812		JP	Y
2	00922100	45574554	23307812		EP	Y
3	60042329	45574554	23307812		DE	Y
4	89107574	0	23307812		TW	N
5	33456899	0	23307812		US	N

EARLIEST_FILING_DATE

This refers to the **earliest date** on which any priority application linked to this patent was filed. If an application claims priority from an earlier application, this field helps establish that earlier date as the key date for assessing novelty. In particular, this attribute indicates the earliest date of the filing dates of the application itself, its international application, its Paris Convention priority applications, the applications with which it is related via technical relations and its application continuations.

The earliest filing date refers to the date of the first application to be filed among all the different applications belonging to the same DOCDB family. This can be clearly seen retriving the `appln_filing_date` and the `earliest_filing_date` of the applications ordered by `docdb_family_id`. We randomly select one that has more than one application. We see that all the applications belonging to the same DOCDB family have the same earliest filing date.

In [52]:
```
earl_in_fam = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.appln_nr,
    TLS201_APPLN.docdb_family_id,
    TLS201_APPLN.appln_filing_date,
    TLS201_APPLN.earliest_filing_date
).filter(
    TLS201_APPLN.appln_id < 900000000,
    TLS201_APPLN.docdb_family_id == 63669288
)

earl_in_fam_df = patstat.df(earl_in_fam)
earl_in_fam_df
```

Out[52]:

	appln_id	appln_nr	docdb_family_id	appln_filing_date	earliest_filing_date
0	528351961	201916698606	63669288	2019-11-27	2016-05-09
1	506638299	201816143286	63669288	2018-09-26	2016-05-09
2	500778505	201815973341	63669288	2018-05-07	2016-05-09
3	512778702	201816224724	63669288	2018-12-18	2016-05-09
4	506420046	201816143305	63669288	2018-09-26	2016-05-09
...	...	...	...	...	...
102	512776504	201816226566	63669288	2018-12-19	2016-05-09
103	528346584	201916697024	63669288	2019-11-26	2016-05-09
104	511593416	201816230366	63669288	2018-12-21	2016-05-09
105	528345122	201916698668	63669288	2019-11-27	2016-05-09
106	514745252	201816236033	63669288	2018-12-28	2016-05-09

107 rows × 5 columns

EARLIEST_FILING_YEAR

Similar to the field above, this extracts the **year** from the earliest filing date.

Showing the filing year and the earliest filing year, we can see that the two differs in many cases.

In [53]:
```
earl_fil_year = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.appln_filing_year,
    TLS201_APPLN.earliest_filing_year
).order_by(
    TLS201_APPLN.appln_auth
).limit(500000)

earl_fil_year_df = patstat.df(earl_fil_year)
earl_fil_year_df
```

Out[53]:

	appln_id	appln_auth	appln_filing_year	earliest_filing_year
0	930132237		9999	9999
1	930129469	AD	9999	9999
2	930129284	AD	9999	9999
3	930131303	AD	9999	9999
4	930132491	AD	9999	9999
...	...	...	...	...
499995	1013702	AT	2001	2000
499996	319029539	AT	2005	2004
499997	1141405	AT	1983	1982
499998	1176792	AT	1987	1986
499999	1127800	AT	1982	1981

500000 rows × 4 columns

EARLIEST_PUBLN_DATE / EARLIEST_PUBLN_YEAR

These fields record the **date and year** when the patent was first published. Patent applications are typically published 18 months after the filing date unless the applicant requests early publication or the application is withdrawn before publication.

In [54]:
```
earl_pub = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.earliest_publn_date,
    TLS201_APPLN.earliest_publn_year
).order_by(
    TLS201_APPLN.appln_auth
).limit(500000)

earl_pub_df = patstat.df(earl_pub)
earl_pub_df
```

Out[54]:

	appln_id	appln_auth	earliest_publn_date	earliest_publn_year
0	930132237		9999-12-31	9999
1	930130487	AD	9999-12-31	9999
2	930133292	AD	9999-12-31	9999
3	930131328	AD	9999-12-31	9999
4	930131303	AD	9999-12-31	9999
...	...	...	...	...
499995	900042976	AT	9999-12-31	9999
499996	1018204	AT	2006-09-15	2006
499997	896592	AT	1932-02-25	1932
499998	910116	AT	1935-01-25	1935
499999	692977	AT	1909-11-25	1909

500000 rows × 4 columns

EARLIEST_PAT_PUBLN_ID

This is the **unique identifier** for the earliest publication of the patent. It links the application to the publication event, which is often the first time the public gets to see the invention.

Let's simply show the ID's together with the earliest filing date and the earliest publication date. Obviously, the publication date is always later than the filing one.

In [55]:
```
earl_pat_id = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.earliest_pat_publn_id,
    TLS201_APPLN.earliest_filing_date,
    TLS201_APPLN.earliest_publn_date
).filter(
    TLS201_APPLN.appln_id < 900000000
).limit(500000)

earl_pat_id_df = patstat.df(earl_pat_id)
earl_pat_id_df
```

Out[55]:

	appln_id	earliest_pat_publn_id	earliest_filing_date	earliest_publn_date
0	339864512	383355894	9999-12-31	1869-10-28
1	339865721	383357098	9999-12-31	1872-01-26
2	339866209	383357588	9999-12-31	1872-11-21
3	339867104	383358487	9999-12-31	1873-09-10
4	339867373	383358756	9999-12-31	1874-01-05
...	...	...	...	...
499995	596646454	596646455	2023-03-24	2023-08-04
499996	596357774	596357775	2023-03-24	2023-07-28
499997	604490822	604490823	2023-03-24	2024-01-09
499998	595761508	595761509	2023-03-27	2023-07-18
499999	599473842	599473843	2023-03-27	2023-09-29

500000 rows × 4 columns

GRANTED

This is a **binary field** that indicates whether the application has been granted (Y for yes, N for no). A granted patent means the application successfully passed the examination phase and the patent office awarded the patent right.

Granted patents in 2022 for each application authority

To explore this attribute, an interesting analysis may be looking at the gap between filed applications and granted patents for each application authority in, for example, 2022. We first count the applications filed in 2022 in each application authority, then we use the result as a subquery and from that we compute the number of granted patents, that is filtering the applications with the `granted` attribute equal to 'Y'. Both in the subquery and in the query we need to filter the applications filed in 2022.

In [56]:

```
# Count the number of applications id for each appication authori
ty in 2022
filed_appln_2022 = db.query(
    TLS201_APPLN.appln_auth,
    func.count(TLS201_APPLN.appln_id).label('filed_applications')
).filter(
    TLS201_APPLN.appln_filing_year == 2022  # Filter the applicat
ions filed in 2022
).group_by(
    TLS201_APPLN.appln_auth
).subquery()  # Create subquery

# Count the granted applications
grant_auth_2022 = db.query(
    TLS201_APPLN.appln_auth,
    func.count(TLS201_APPLN.granted).label('granted_patents'),
    filed_appln_2022.c.filed_applications
).filter(
    TLS201_APPLN.granted == 'Y',  # Filter granted applications o
nly
    TLS201_APPLN.appln_filing_year == 2022,  # Again filter appli
cations filed in 2022
    TLS201_APPLN.appln_auth == filed_appln_2022.c.appln_auth
).group_by(
    TLS201_APPLN.appln_auth,
    filed_appln_2022.c.filed_applications
).order_by(
    func.count(TLS201_APPLN.granted).desc()
)

grant_auth_2022_df = patstat.df(grant_auth_2022)
grant_auth_2022_df
```

Out[56]:

	appln_auth	granted_patents	filed_applications
0	CN	2576172	3876190
1	US	89827	376508
2	JP	59413	196156
3	KR	38847	128795
4	TW	29396	57956
5	DE	10639	43396

6	ZA	7816	7959
7	CA	3493	26251
8	EP	2723	79813
9	ES	2429	3147
10	NL	2419	2775
11	AU	2218	21969
12	LU	1757	1828
13	CZ	1099	1246
14	BE	701	756
15	GB	686	16556
16	AT	654	1096
17	FR	608	7923
18	FI	303	949
19	SK	242	338
20	DK	204	738
21	GR	200	670
22	PL	189	2291
23	SE	187	1107
24	BG	185	252
25	BR	183	5988
26	RU	144	614
27	NO	132	985
28	HU	119	384
29	IL	104	9791
30	SI	101	122
31	MD	86	101
32	CH	74	839
33	PT	68	347
34	LT	59	101
35	CL	45	3056
36	SA	44	53
37	UY	41	275
38	RS	40	98
39	IE	31	88

40	UA	30	2047
41	MA	30	138
42	GE	29	30
43	AR	18	2753
44	LV	14	63
45	EE	14	18
46	MY	6	98
47	MT	4	5
48	MC	2	2
49	RO	1	531

Percentage of granted patents over the total number of filing per application authority in 2022

At this point, we can compute the percentage of granted patents over the total number of filings. Let's create a subquery from the last query so that we can use its attributes to accomplish our computations.

In [57]:
```
# Generate subquery
subq = grant_auth_2022.subquery()

# Compute the percentages
grant_perc = db.query(
    subq.c.appln_auth,
    (100 * subq.c.granted_patents / subq.c.filed_applications).la
bel('per_granted_pats')
).order_by(
    (100 * subq.c.granted_patents / subq.c.filed_applications).de
sc()
)

grant_perc_df = patstat.df(grant_perc)
grant_perc_df['per_granted_pats'] = grant_perc_df['per_granted_pa
ts'].astype(int)
grant_perc_df
```

Out[57]:

	appln_auth	per_granted_pats
0	MC	100
1	ZA	98
2	GE	96
3	LU	96

4	BE	92
5	CZ	88
6	NL	87
7	MD	85
8	SA	83
9	SI	82
10	MT	80
11	EE	77
12	ES	77
13	BG	73
14	SK	71
15	CN	66
16	AT	59
17	LT	58
18	TW	50
19	RS	40
20	IE	35
21	FI	31
22	HU	30
23	JP	30
24	KR	30
25	GR	29
26	DK	27
27	DE	24
28	US	23
29	RU	23
30	LV	22
31	MA	21
32	PT	19
33	SE	16
34	UY	14
35	NO	13
36	CA	13
37	AU	10

38	CH	8
39	PL	8
40	FR	7
41	MY	6
42	GB	4
43	EP	3
44	BR	3
45	CL	1
46	UA	1
47	IL	1
48	AR	0
49	RO	0

Again, the percentages must be read in the light of the total number of applications filed. Indeed, the applications authority with 100% of applications granted are the ones with a low number of applications filed.

DOCDB_FAMILY_ID / INPADOC_FAMILY_ID

These fields represent the **patent family identifiers** in different databases:

- **DOCDB_FAMILY_ID**: The family ID according to the EPO's DOCDB system, which groups patent applications that are related by common priority claims.
- **INPADOC_FAMILY_ID**: Similar to the DOCDB family but using the INPADOC data from WIPO, which can include additional legal status information.

Applications belong to only one DOCDB family

An important concept about DOCDB families is that each patent application in PATSTAT belongs to one and only one DOCDB patent family. To demonstate this fact we can simply count the distinct number of `docbd_family_id` s grouped by `appln_id` .

Again, better to switch to 'TEST'.

In [58]:
```
patstat = PatstatClient(env='TEST')

db = patstat.orm()
```

In [59]:
```
docdb_fam = db.query(
    TLS201_APPLN.appln_id,
    func.count(TLS201_APPLN.docdb_family_id.distinct()).label('dist_docdb_fam')
).group_by(
    TLS201_APPLN.appln_id
).order_by(
    func.count(TLS201_APPLN.docdb_family_id.distinct()).desc()
)

docdb_fam_df = patstat.df(docdb_fam)
docdb_fam_df
```

Out[59]:

	appln_id	dist_docdb_fam
0	23307078	1
1	23307812	1
2	47805262	1
3	3150828	1
4	3084616	1
...	...	...
323703	604951821	1
323704	605752605	1
323705	605759471	1
323706	602886417	1
323707	604330031	1

323708 rows × 2 columns

Ordering by distinct `docdb_family_id` in descending order we get 1 also at the top rows, proving the claim.

Now we show that the vice versa is not true, otherwise the two attributes would provide the same information.

In [60]:
```
applnxfam = db.query(
    TLS201_APPLN.docdb_family_id,
    func.count(TLS201_APPLN.appln_id.distinct()).label('distinct applications')
).group_by(
    TLS201_APPLN.docdb_family_id
).order_by(
    func.count(TLS201_APPLN.appln_id.distinct()).desc()
)

applnxfam_df = patstat.df(applnxfam)
applnxfam_df
```

Out[60]:

	docdb_family_id	distinct applications
0	47997543	72
1	63669288	59
2	45509505	49
3	34685019	46
4	26009137	44
...	...	...
256865	89511992	1
256866	89511934	1
256867	89714467	1
256868	89714876	1
256869	88968466	1

256870 rows × 2 columns

This property suggests a direct conclusion that affects the modus operandi to follow when performing any kind of analysis concerning the impact of an invention: counting the `appln_id` s grouped by country is counting the number of inventions protected in each country. This is different from counting the `docdb_family_id` s, that results in the actual number of inventions, that is what we really mind when conducting a study on the innovative impact.

For INPADOC families, this is true as well.

In [61]:
```
inpadoc_fam = db.query(
    TLS201_APPLN.appln_id,
    func.count(TLS201_APPLN.inpadoc_family_id.distinct()).label('
dist_inpadoc_fam')
).group_by(
    TLS201_APPLN.appln_id
).order_by(
    func.count(TLS201_APPLN.inpadoc_family_id.distinct()).desc()
)

inpadoc_fam_df = patstat.df(inpadoc_fam)
inpadoc_fam_df
```

Out[61]:

	appln_id	dist_inpadoc_fam
0	23307078	1
1	23307812	1
2	47805262	1
3	3150828	1
4	3084616	1
...	...	...
323703	604951821	1
323704	605752605	1
323705	605759471	1
323706	602886417	1
323707	604330031	1

323708 rows × 2 columns

INPADOC families are bigger than DOCDB families

What does change is the number of applications that an INPADOC family can contain, that is higher than the number of applications included by DOCDB families. This is because INPADOC families comprise applications with related but possibly different technical descriptions, while DOCDB families include applications with identical technical description only. We can also show that for each INPADOC family there is **at least** one DOCDB family associated to it.

In [62]:
```
applnxinpafam = db.query(
    TLS201_APPLN.inpadoc_family_id,
    func.count(TLS201_APPLN.appln_id.distinct()).label('distinct applications'),
    func.count(TLS201_APPLN.docdb_family_id.distinct()).label('distinct DOCDB families')
).group_by(
    TLS201_APPLN.inpadoc_family_id
).order_by(
    func.count(TLS201_APPLN.docdb_family_id.distinct()).desc()
)

applnxinpafam_df = patstat.df(applnxinpafam)
applnxinpafam_df
```

Out[62]:

	inpadoc_family_id	distinct applications	distinct DOCDB families
0	98645	147	123
1	2715465	89	61
2	318176609	104	40
3	3283	144	39
4	356227	57	36
...	...	...	...
251510	604951886	1	1
251511	604951821	1	1
251512	605752605	1	1
251513	605759471	1	1
251514	602886417	1	1

251515 rows × 3 columns

DOCDB_FAMILY_SIZE

This tells us the **size of the patent family**, meaning how many applications are related through priority claims. A larger family size could indicate that the invention is being pursued in multiple jurisdictions, suggesting its commercial importance.

In [63]:
```
patstat = PatstatClient(env='PROD')

db = patstat.orm()
```

In [64]:
```
size = db.query(
    TLS201_APPLN.docdb_family_id,
    TLS201_APPLN.docdb_family_size
).filter(
    TLS201_APPLN.appln_id < 900000000
).order_by(
    TLS201_APPLN.docdb_family_size
).limit(500000)

size_df = patstat.df(size)
size_df
```

Out[64]:

	docdb_family_id	docdb_family_size
0	24674324	1
1	21777466	1
2	34366971	1
3	40765395	1
4	32918711	1
...	...	...
499995	86836326	1
499996	51121054	1
499997	82667201	1
499998	21951806	1
499999	11917403	1

500000 rows × 2 columns

It is worth to mention that al the artificial applications, i.e. the ones with `appln_id` greater than 900 millions, have the DOCDB family ID equal to `appln_id` .

In [65]:
```
dummy = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.docdb_family_id
).filter(
    (TLS201_APPLN.appln_id == 0) | (TLS201_APPLN.appln_id > 90000
0000)
)

dummy_df = patstat.df(dummy)
dummy_df
```

Out[65]:

	appln_id	docdb_family_id
0	900462579	900462579
1	960027498	960027498
2	931406836	931406836
3	900959352	900959352
4	930505777	930505777
...	...	...
11145892	902330624	902330624
11145893	903109253	903109253
11145894	901588152	901588152
11145895	905903456	905903456
11145896	906097245	906097245

11145897 rows × 2 columns

NB_CITING_DOCDB_FAM

This field shows the **number of citing patents** that reference this application’s DOCDB family, indicating the technological relevance or impact of the invention.

Total number of citations for application authority

Let's see what is the total number of citations collected in each application authorty.

In [66]:
```
citing = db.query(
    TLS201_APPLN.appln_auth,
    func.sum(TLS201_APPLN.nb_citing_docdb_fam).label('total_citat
ions')
).group_by(
    TLS201_APPLN.appln_auth
).order_by(
    func.sum(TLS201_APPLN.docdb_family_size).desc()
)

citing_df = patstat.df(citing)
citing_df
```

Out[66]:

	appln_auth	total_citations
0	US	275088682
1	CN	92620335
2	JP	103998470
3	EP	80302676
4	WO	62896429
...	...	...
202	VG	0
203	WS	0
204	MP	0
205	XX	0
206		0

207 rows × 2 columns

Average number of citations per DOCDB family for each application authority

This analysis does not keep track of what enabled such authorities to reach these numbers: a few very impactful applications that raised the total number or a generally quite high number of citations for each family related to these authorities? It also depends on the number of families that each authority is associated with. We can investigate this by repeating the same process but computing the average number of citations per application authority instead of the sum.

In [67]:
```
avg_citing = db.query(
    TLS201_APPLN.appln_auth,
    func.avg(TLS201_APPLN.nb_citing_docdb_fam).label('avg_num_citations')
).group_by(
    TLS201_APPLN.appln_auth
).order_by(
    func.avg(TLS201_APPLN.nb_citing_docdb_fam).desc()
)

avg_citing_df = patstat.df(avg_citing)
avg_citing_df['avg_num_citations'] = avg_citing_df['avg_num_citations'].astype(int)
avg_citing_df
```

Out[67]:

	appln_auth	avg_num_citations
0	ME	40
1	CY	35
2	HK	31
3	DZ	28
4	SV	27
...	...	...
202	CI	0
203	UG	0
204	DM	0
205	SR	0
206	MZ	0

207 rows × 2 columns

A statistic at macro level provides meaningful insights only if the total number of samples is high enough. For this reason, we check the total number of DOCDB families to which each application authority is linked.

In [68]:
```
num_fam = db.query(
    TLS201_APPLN.appln_auth,
    func.count(TLS201_APPLN.docdb_family_id).label('num_docdb_fam
ilies')
).group_by(
    TLS201_APPLN.appln_auth
).order_by(
    func.count(TLS201_APPLN.docdb_family_id).desc()
)

num_fam_df = patstat.df(num_fam)
num_fam_df
```

Out[68]:

	appln_auth	num_docdb_families
0	CN	38349201
1	JP	21867386
2	US	18865932
3	DE	7396519
4	KR	5360107
...	...	...
202		1
203	WS	1
204	GQ	1
205	WF	1
206	SO	1

207 rows × 2 columns

Median of citations per DOCDB family for each application authority

Nevertheless, the average is not the best statistic that we can use in this context. To explain why, let's imagine a toy example. Suppose that there is an authority with applications filed belonging to two DOCDB families: one is cited a few times, while the other one is cited hundreds of times. The average in this case would be some number in the middle, hence not representative of neither of the two families. To cope with this issue we can use the median instead. Indeed, this value returns the middle number among the ones present in the sample.

Since there is not a command in ORM to directly compute the median, we have to do it manually. To do so, we start counting the number of families to which each application authority is linked. If this number is odd we just take the middle value, otherwise we take the average between the two middle values.

In [69]:
```
# Count the number of families for each application authority
count_citing = db.query(
    TLS201_APPLN.appln_auth,
    func.count(TLS201_APPLN.docdb_family_id).label('families_coun
t')
).group_by(
    TLS201_APPLN.appln_auth
).order_by(
    func.count(TLS201_APPLN.docdb_family_id)
)

count_citing_df = patstat.df(count_citing)

# Create an empty list that will be filled with the medians of fa
milies citations for each authority
medians = []

# Run through the application authorities in the dataframe just c
reated while keeping track of the row index
for (i, auth) in zip(count_citing_df.index, count_citing_df['appl
n_auth']):
    count = count_citing_df.iloc[i,1]  # count is the variable co
ntaining the number of DOCDB families of the current authority au
th
    # Check if count is odd or even
    if count % 2 == 1:
        # Odd case: get the middle value
        median_query = db.query(TLS201_APPLN.nb_citing_docdb_fa
m).filter(TLS201_APPLN.appln_auth == auth).order_by(TLS201_APPLN.
nb_citing_docdb_fam).offset(count // 2).limit(1)
        result = median_query.all()
        median_value = result[0][0]
        medians.append(median_value)
    else:
        # Even case: get the two middle values
        median_query = db.query(TLS201_APPLN.nb_citing_docdb_fa
m).filter(TLS201_APPLN.appln_auth == auth).order_by(TLS201_APPLN.
nb_citing_docdb_fam).offset(count // 2 - 1).limit(2)
        result = median_query.all()
        # Compute the average of the two middle values
        median_value = sum([res[0] for res in result]) / 2.0
        medians.append(median_value)

# Create a dataframe with two columns: the application authoritie
s and the corresponding median values of citations
median_citing_df = pd.DataFrame({'appln_auth': count_citing_df['a
ppln_auth'], 'median_of_citation': medians})
```

```
# Convert the median values to integer type
median_citing_df['median_of_citation'] = median_citing_df['median_of_citation'].astype(int)
# Sort by median in descending order (ascending=False)
median_citing_df.sort_values(by='median_of_citation', ascending=False, inplace=True)
# Do not sort the index
median_citing_df = median_citing_df.reset_index(drop=True)
median_citing_df
```

Out[69]:

	appln_auth	median_of_citation
0	ME	20
1	CY	15
2	HK	14
3	DZ	13
4	SV	13
...	...	...
202	XN	0
203	MO	0
204	NG	0
205	PY	0
206	BI	0

207 rows × 2 columns

We do not have such extreme cases as the one in the toy example, hence the numbers observed in the median table are a bit different from the ones in the average table but it does not change the ranking. The evidence here is that these two tables show a different story from the table of total applications. Indeed, we can see that while CN, US, EP and WO are the application authorities with the highest numbers of citations, the highest averages and medians are found in smaller authorities. This tells us a key fact about patents market: when an invention is truly innovative (and supposedly will be cited more times) it will be protected in more countries, even the smallest ones. Conversely, in bigger countries we can find inventions with different level of innovation. This results in small countries collecting less filing and so less citations but quite innovative inventions on average. One can check the size of the most cited families to confirm this hypothesis but this analysis is beyond the scope of this course.

NB_APPLICANTS / NB_INVENTORS

These fields count the **number of applicants** and **number of inventors** associated with the application. A single application may have multiple inventors or applicants (such as a corporation and its researchers).

If no publication of the application contains applicant names in Latin characters, then `nb_applicants` will be zero. Similarly, if no publication of the application contains inventor names in Latin characters, then `nb_inventors` will be zero.

In PATSTAT quite many applications with either `nb_applicants` or `nb_inventors` equal to 0 can be found. This can be checked with a simple query.

Since these are just illustrative examples, let's work in 'TEST'.

In [70]:
```
patstat = PatstatClient(env='TEST')

db = patstat.orm()
```

In [71]:
```
no_applicant_inv = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.nb_applicants,
    TLS201_APPLN.nb_inventors
).filter(
    (TLS201_APPLN.nb_applicants == 0) | (TLS201_APPLN.nb_inventor
s == 0),
    TLS201_APPLN.appln_id < 900000000
).order_by(
    TLS201_APPLN.nb_applicants
)

no_applicant_inv_df = patstat.df(no_applicant_inv)
no_applicant_inv_df
```

Out[71]:

	appln_id	appln_auth	nb_applicants	nb_inventors
0	23307078	GB	0	0
1	23307812	GB	0	0
2	47805262	US	0	0
3	3150828	BE	0	0
4	3084616	BE	0	0
...	...	...	...	...
10541	570126409	DE	4	0
10542	557220105	IL	5	0
10543	501706837	DE	9	0
10544	566485039	DE	12	0
10545	405239188	DE	23	0

10546 rows × 4 columns

Some applications do not have inventors registered, often because they do not want to share their names. What is stranger is to not have any applicants. Yet this can happen.

In [72]:
```
no_applicant = db.query(
    TLS201_APPLN.appln_id,
    TLS201_APPLN.appln_auth,
    TLS201_APPLN.nb_applicants,
    TLS201_APPLN.nb_inventors
).filter(
    TLS201_APPLN.nb_applicants == 0,
    TLS201_APPLN.nb_inventors != 0,
    TLS201_APPLN.appln_id < 900000000
).order_by(
    TLS201_APPLN.nb_applicants
)

no_applicant_df = patstat.df(no_applicant)
no_applicant_df
```

Out[72]:

	appln_id	appln_auth	nb_applicants	nb_inventors
0	20868306	FR	0	1
1	19351006	FR	0	1
2	19384289	FR	0	3
3	19372853	FR	0	2
4	19381110	FR	0	1
...	...	...	...	...
1918	587515270	CL	0	3
1919	587515278	CL	0	2
1920	592390028	FI	0	3
1921	596542825	TW	0	1
1922	599559884	TW	0	1

1923 rows × 4 columns

It can also be observed that the number of inventors linked to an application is usually higher than the corresponding number of applicants.

In [73]:
```
more_appl = db.query(
    func.count(TLS201_APPLN.appln_id).label('occurrencies')
).filter(
    TLS201_APPLN.nb_applicants > TLS201_APPLN.nb_inventors
)

occurrencies = patstat.df(more_appl)
occurrencies = occurrencies['occurrencies'].item()
print("We find "+str(occurrencies)+" applications with more appli
cants than inventors.")
```

```
We find 28135 applications with more applicants than inventors.
```

In [ ]:
```
```