

# Data Engineering Project

Azure stack

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# 1. Business Concept

Our business goal is to get a better understanding of open-source technology trends. We want to understand which are the "hot" projects and see how the monitored projects/companies are performing compared to others.

Our goal is to better understand the development of the open source tech market - we want to answer these questions using several data sources.

#### **Datasets:**

We will use the following freely available datasets provided by BigQuery. (Already extracted from BigQuery and stored in another location):

- Github
- StackOverflow

#### **Configuration:**

We will get the configuration data from an REST API

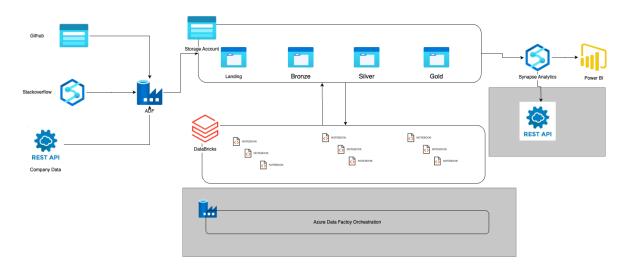
The target is to create a common data repository for these datasets, load them into a central database, apply the necessary transformations and create useful insights from the available data, that is presentable with Data Visualizations.

#### Example Question:

Check if there is a correlation between a trending Stackoverflow post about a tool and the Github stars statistic.



## 2. Architecture



We use the medallion lakehouse architecture, with the following layers in it:

- **landing layer**: target of the ingestion pipelines, data is untyped, untransformed here, contains source data "as-is" (loaded with an ADF copy activity)
- bronze/raw layer: source data with minimal transformations but already in delta format (loaded with Databricks Notebooks called from an ADF pipeline)
- **silver/enriched layer**: cleaned and transformed data in delta format (loaded with Databricks Notebooks called from an ADF pipeline)
- gold/curated layer: presentation layer which contains aggregated data according to report needs (loaded with Databricks Notebooks called from an ADF pipeline)
- **serving layer**: a view layer in Synapse SQL Serverless Pool on top of the gold layer data which can be used as any other standard database by BI tools and analysts (loaded with Databricks Notebooks called from an ADF pipeline)

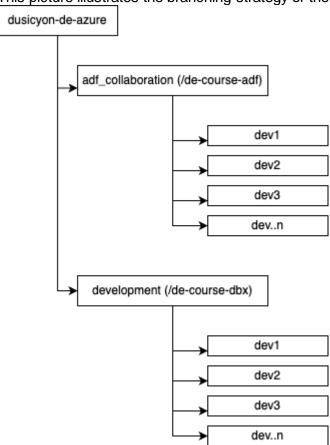
Technically the end goal is to create a Master Pipeline in Azure Data Factory with one "p\_load\_date" parameter which triggered with a specific date loads all of that date"s source data from their original location through all of the layers of our delta lake. We will serve the gold layer data with Synapse Views in SQL serverless Pool on top of it for BI tools and analysts.





# 3. Branching strategy

We use github as source and version control service. The main idea is that there will be one root branch for the ADF and one for the Databricks. Everybody will have a separate branch under these branches for the development. The two root branch have been already created. This picture illustrates the branching strategy of the project.





# 4. Ingestion (Landing layer)

There are some suggestion to create and configure services for the project. Mainly you can use the services you already created for learning purposes, but some configuration (git, folders, etc) is necessary. So you can ignore the create services part, but the configuration is essential!

The ingestion part of the project provide the data for the processing in the source format. This means in this case we pull data from the data sources and store it on the storage account. This part of the project helps to understand the following skills:

- Setup an architecture for a Delta Lake project
- Set security settings between Azure services
- Use Git integration
- Create Delta Lake folder structure
- Pull data from multiple type of datasources
- Store data to Landing layer
- Create flow pipeline for ingestion

#### **Expected result**

We expect the following outcome of the ingestion:

- Have the architecture
- Create folder structure on Storage Account
- Pull data from the sources
- · Store data in csv or in json format
- Create an ADF pipeline for orchestration

We will use data for three date.

- 20220731
- 20220831
- 20220930

If you call the API, or the parametrized flow you should use these dates. The first one is the initial load, the second and the third are the incrementals.

## 4.1 List of tasks

- Create an <u>Azure Data Lake Storage Account</u>
  - o you can skip if you already have created
- Create an Azure Data Factory service
  - you can skip if you already have created
- Integrate your ADF with your git repo
- On the Azure portal <u>add Storage Blob Contributor</u> role to the ADF managed identity on the Storage Account you created
- Create Linked Services for sources in ADF and test if the connections are working:
  - Stackoverflow:



- Synapse linked service
- Fully qualified domain name: de-course-synw-ondemand.sql.azuresynapse.net
- Database name: external db
- Authentication type: SQL Authentication
  - User name: destudentPassword: Stud123
- GitHub:
  - Azure Data Lake Storage gen2 linked service
  - Authentication type: Account key
  - URL: https://decoursesacc.dfs.core.windows.net
  - Storage account key:
     VUFSrvMVgBg6u4uqwrBpN8qM9NpS9pwHMbKQCtsZl8bVlmHFBpx1j
     Yir4Jp3wTEpmVudEYt+BalL+AStDN7ulw==
- Company\_detail:
  - REST linked service
  - API: https://de-course-ingest-api.azurewebsites.net/api/
  - Anonymous authentication
- Create Linked Service for target storage in ADF and test if the connection is working:
  - Azure Data Lake Storage gen2 linked service
  - Authentication type: System Assigned Managed Identity
  - From subscription chose your storage account
- Create a dataset for each of the source and target files/tables in ADF
  - it is recommended to organize the datasets in folder structure
  - you can import the schema of the sources but it is not necessary (the ingestion pipelines will be more dynamic if you do not specify the schema)
  - Stackoverflow datasets:
    - Source StackoverflowPostQuestions:
      - Synapse dataset from Stackoverflow's synapse linked service
      - Table name: stackoverflow.stackoverflow post questions
    - Source StackoverflowPostAnswers:
      - Synapse dataset from Stackoverflow's synapse linked service
      - Table name: stackoverflow.stackoverflow\_post\_answers
    - Landing\_StackoverflowPostQuestions:
      - CSV dataset from the target storage linked service
      - file path: landing/stackoverflow/stackoverflow\_post\_questions.csv
      - this file will be overwritten with every ingestion pipeline run
    - Landing StackoverflowPostAnswers:
      - CSV dataset from the target storage linked service
      - file path: landing/stackoverflow/stackoverflow\_post\_answers.csv
      - this file will be overwritten with every ingestion pipeline run
  - o GitHub datasets:
    - Source\_GitHubArchiveDay:
      - JSON dataset from the source storage linked service
      - file path: external/github/githubarchiveday\_yyyymmdd.json
      - yyyymmdd should be a @p\_load\_date parameter in the dataset
    - Landing\_GitHubArchiveDay:
      - JSON dataset from the target storage linked service
      - file path: landing/github/githubarchiveday yyyymmdd.json
      - yyyymmdd should be a @p\_load\_date parameter in the dataset



- CompanyDetail datasets:
  - Source\_CompanyDetail:
    - REST dataset from the source REST linked service
    - relative URL: get\_company\_data\_api?p\_load\_date=yyyymmdd
    - yyyymmdd should be a @p\_load\_date parameter in the dataset
  - Landing\_CompanyDetail:
    - JSON dataset from the target storage linked service
    - file path: landing/company\_detail/company\_detail\_yyyymmdd.json
    - yyyymmdd should be a @p\_load\_date parameter in the dataset
- Create 4 pipelines to copy all of the sources of a given date to the landing layer:
  - parameter: @p\_load\_date (in case of stackoverflow the date parameter is not needed)
  - variable: @v\_load\_date = @p\_load\_date (if missing, yesterday should be the default value)
  - the pipelines should contain the following two activities:
    - set variable
    - copy data activity: copy from source to landing dataset
- Create an "Ingestion" flow pipeline with one "p\_load\_date" parameter and the following activities:
  - o set "v load date" variable
  - simply add 4 execute pipeline activity to run your previously created pipelines (connect all of them right after the set variable activity so ingestion can run in parallel mode)

## 4.2 Optional tasks

- Create dynamic stackoverflow datasets, where the table name/file name is a parameter
- Add an ingestion datetime column to the stackoverflow target datasets so you can see when was the data loaded from the source database
- Copy the github and company data sources to the following folder structure:
  - landing/github/yyyy/mm/dd/github\_yyyymmdd.json
  - landing/company\_detail/yyyy/mm/dd/company\_detail\_yyyymmdd.json
  - where the yyyy/mm/dd values should be set from the @p\_load\_date parameter
- Improve your "Ingestion" flow pipeline with the following logics:
  - o delete the 4 direct execute pipeline activities
  - create an array which contains the 4 source file names or a config file with the file names and the source type (github/stackoverflow/company\_detail) in it
  - create a for each activity which iterates through the items in parallel mode
  - inside the for each activity create a switch activity which executes the right ingestion pipeline for all of the file names (for example if the source type or the beginning of the file name is stackoverflow execute the stackoverflow ingestion pipeline)
  - probably this task in this form does not make sense for this 4 source files but in case of more source files this approach can significantly simplify your ingestion pipeline
- Create a log delta table, and insert one row into it at every pipeline run start and one
  in the end



- possible logging informations: pipeline name, run ID, file name, start time, end time, status, error message, etc.
- use ADF data flow to write the logs to a delta table without Databricks
  - source should be an empty dummy file
  - create the data for logging during runtime with derived columns defined from parameter values
  - sink should be a delta type inline dataset
- At the end of the "Ingestion" flow pipeline create an email notification which sends you an email after every run with the basic run results in it:
  - o use Web Activity with Logic Apps to do it
  - o a useful video on the subject: https://www.youtube.com/watch?v=zyqf8e-6u4w
  - this task can be time consuming so most likely there will be no time to do it now but it is present in the optional task list so you know that it is worth dealing with the topic in the future when you will have time for it

#### 4.3 Materials

## 4.3.1 Storage Account

#### Tips:

- Storage account names must be between 3 and 24 characters in length and may contain numbers and lowercase letters only.
- Your storage account name must be unique within Azure. No two storage accounts can have the same name.
- Enable hierarchical namespace to use this storage account for Azure Data Lake Storage Gen2 workloads
- For cost saving purpose:
  - Disable soft deletes
  - Set Local redundancy
- Download Azure Storage Explorer if you want to manage your Azure cloud storage resources from your desktop

#### Current project structure:

- decoursesacc storage account
  - landing container
  - bronze container
  - silver container
  - gold container
  - system container
  - sandbox container

#### Future modification options:

- We create only one environment at start (for testing and production purpose we should create separate storage accounts)
- In the dev storage account it is also a possible approach to create separate containers for the developers (in that case the bronze/silver/gold layers would be folders in dev environments and containers in test/production environments)
- Landing can be a separate, environment independent storage account

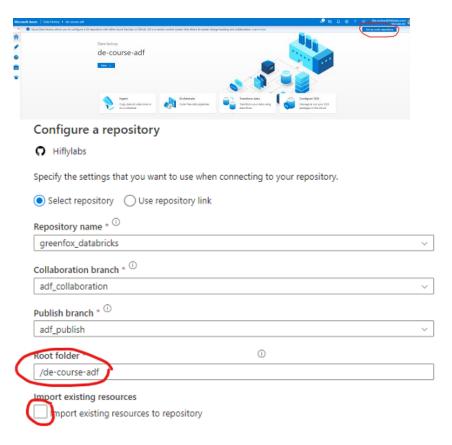


### 4.3.2 Azure Data Factory

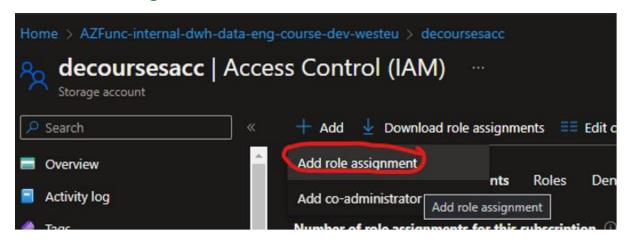
No special configuration is needed.

#### 4.3.2.1 Azure Data Factory git integration

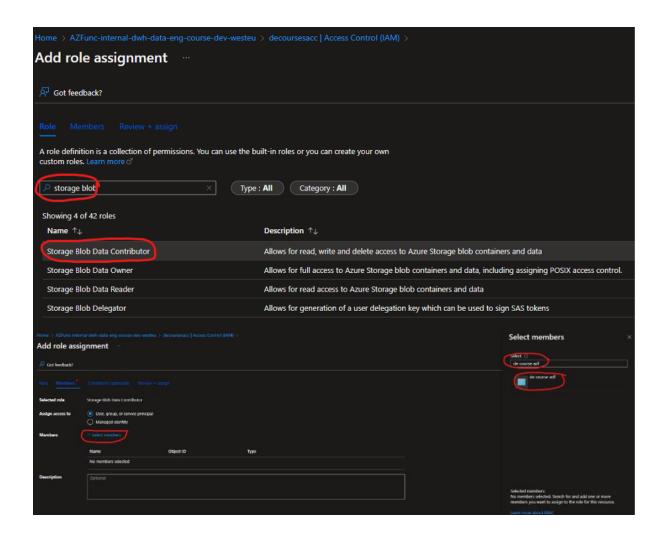
- Log into Github on ADF page
- Set adf\_collaboration branch (everybody should use this)
- Set root folder!
- Create your branch to work on. Give unique name such as adf\_ma. You will need another branch for databricks!



#### 4.3.2.2 BlobStorage contributor access









# 5. Bronze layer

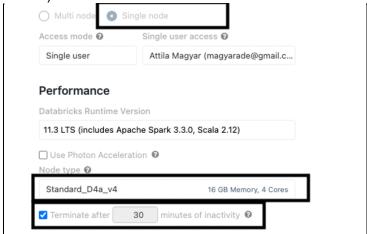
The objective of this phase is to create and load the bronze layer with all the data sources that we previously ingested. The bronze layer's data is almost identical to the original source data but the data is already stored in delta format here.

It's an important note that there is no one, generally accepted solution that can be considered good in all cases. There are plenty of possibilities and choices during the planning and development phases, and most of the time the final solution mode depends on the specific project needs.

Throughout this project the general rule of thumb will be that you should achieve the actual task at least one way, it is completely up to you however, how you do it, as long as the final result is OK. We add one possible approach in the list of tasks and in the optionals tasks part we provide ideas for other alternative solutions.

## 5.1 List of tasks

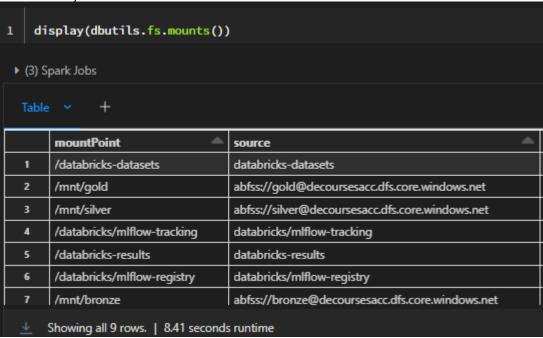
- Create a Databricks workspace (if you have free subscription create the workspace in the region UK South)
  - you can skip if you already have created
- Create a single node cluster and set the automatic termination after 30 minutes of inactivity (if you have free subscription choose Standard\_D4a\_v4 node type for the cluster)



- Integrate your Databricks workspace with your git repo
  - o generate access token with repo scope in github for databricks
  - set git integration in databricks workspace user settings
  - add repo (<u>https://github.com/green-fox-academy/dusicyon-de-azure/</u>) to your databricks workspace
  - create a new feature branch based on the "development" branch (dev\_your-name) and checkout this branch
- Create a "setup" folder in the "de-course-dbx" folder in your feature branch and create a "mount\_storage" notebook in it to mount your Storage Account containers to your <u>Databricks workspace</u> (each container should be a different mount point, for example /mnt/landing)



- register an Azure AD application
- grant storage blob data contributor role to your databricks service principal on your storage account
- create an Azure Key Vault and add the application secret, the client id and the tenant id to it
- o create an Azure Key Vault-backed Secret Scope in Azure Databricks
- mount ADLS to Databricks using Secret Scope (secret scopes are only available in premium databricks tier, so if you have standard tier, you can skip this part and hard code the secrets in the notebook)
- check if all your containers have been mounted



- Create a "bronze\_db" database for the bronze layer tables and specify your bronze container as the location of the database (create a "create\_databases" notebook in the setup folder and write the script in it)
- Create an "etl" folder in your feature branch and create 4 notebooks in it to load the previously ingested data sources to the bronze layer in delta format
  - General data modeling tips:
    - Create a primary key in every table, called \_pk
      - in delta there is no primary key constraint like in SQL database so just create a new column called \_pk based on the business key and in the optional task list we added some suggestions about how to check the primary key columns
      - there is no rule how to make the \_pk column but one possible solution is:
        - when the business key is an id with numeric values the \_pk column can be identical to the id column (id as \_pk) but you should preserve the id column and the \_pk column as well
        - when the business key is not an id create a hash value from the business key
    - Add \_datetime\_utc postfix to every datetime column name and make sure that every datetime is in UTC format



- There is three different technical date column you should use when possible:
  - created\_at\_datetime\_utc: when was the row created in the source system (in company detail json there is no such information)
  - loaded\_at\_datetime\_utc: when was the row loaded to the target table
  - valid\_date: the load date/file date parameter used at loading (business validity date, in stackoverflow dataset it is not mandatory)
- Add is\_ prefix to every boolean type ('Yes'/'No', 1/0) column name and convert it to boolean (true/false).
- prefix the table names with the first letter of the table's layer (for example "b github" for bronze github table)
- General notebook development tips (a possible notebook structure):
  - import sql functions and types

```
from pyspark.sql.types import ...
from pyspark.sql.functions import ...
```

create a widget for the file date parameter

```
dbutils.widgets.text("p_file_date", "")
v_file_date = dbutils.widgets.get("p_file_date")
```

 define the source data schema before reading the data (you can read the source data without defining schema first, explore the dataset and define the schema based on it)

```
github_schema = StructType([
StructField('id', StringType()),

...
]
```

read the data

```
df = spark.read \
schema...
json...
```

transform the data

```
transf_df = df.withColumn("_pk",col("id")) \
...
```

 finally write out the the date to a delta table in the previously created bronze db with overwrite mode

```
final_df = transf_df.select(
col("_pk"),

final_df.write.mode("overwrite").format("delta").saveAsTable("bronze_db.b_github")
```



check the loaded bronze table

```
1 %sql
2 select *
3 from bronze_db.b_github
4 limit 100
```

- in sql notebook fewer step is needed, you can define schema while reading for example or transform and write data in one step (it is also possible to do it in one big step but it will be a less readable code in the end)
- GitHub specific tips:
  - Create the pk field based on the "id" field
  - Make sure that you read the nested fields correctly, and flatten its values to separate columns in the bronze table (for example from the nested repo field you should create 3 columns: repo\_id, repo\_name and repo\_url)
- Stackoverflow specific tips:
  - it is not necessary to use file date parameter for these source data since there is only one source file for all of the dates but you can use the file date parameter and then filter the source data based on it (where creation\_date <= valid\_date)</li>
  - Create the pk field based on the "id" field
- Company detail tips:
  - Create the pk field based on the "organization name" field
  - Create a "tags\_array" field from the source "tags" field
- Create a "landing\_to\_bronze" notebook which run all the bronze ETL notebooks sequentially
- Create a master pipeline in ADF which executes your ingestion flow pipeline and the landing\_to\_bronze databricks notebook sequentially

# 5.2 Optional tasks

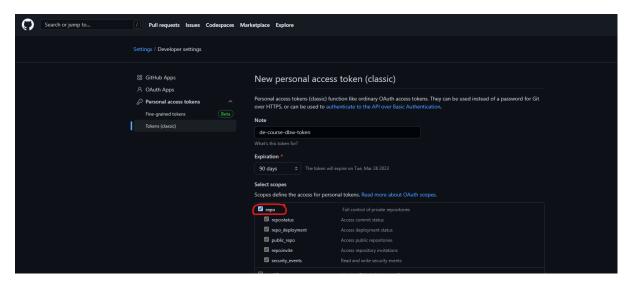
- Create the notebooks with pyspark if you created it with sql first or vice versa
- Try to load the bronze tables with autoloader or COPY INTO command
  - instead of using file date parameter you will load the data that is newly arrived to the landing zone since the last loading
  - add the filename as a new column to the bronze tables because only from it can you determine the valid date information
  - with this loading strategy you will have to use append mode instead of overwrite mode (so in the tasks of the silver layer filter the bronze tables accordingly)
- create the bronze tables before running the etl notebooks in a separate "create\_tables" notebook, and add constraints to the tables for schema enforcement (for example add NOT NULL constraints to the \_pk fields)
- for primary key checking test the uniqueness of the \_pk fields (there is not a built in solution to do that, you should write a separate code logic for uniqueness test)
- allow schema drifting and try out what happens if you modify the structure in one of the landing files



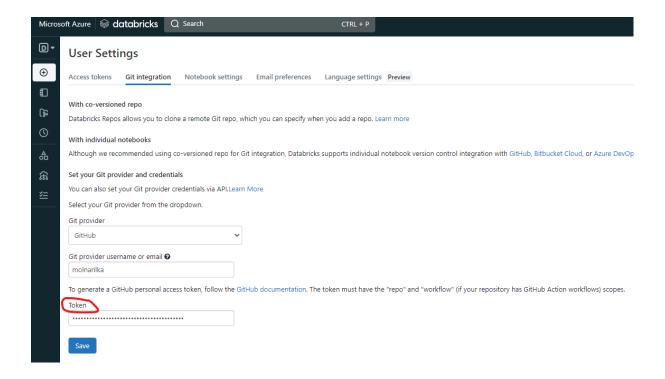
# 5.3 Materials

## 5.3.1 Databricks git integration

 Generate access token with repo scope in github for databricks (Settings/Developer settings/Public access tokens/Token(classic))



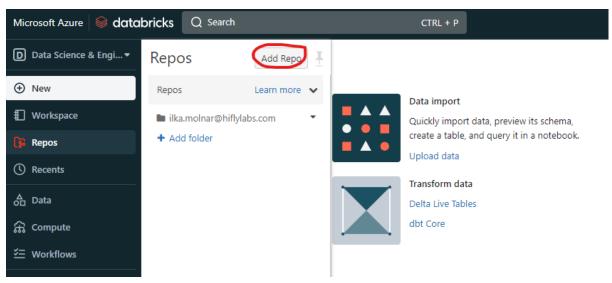
set git integration in databricks workspace user settings

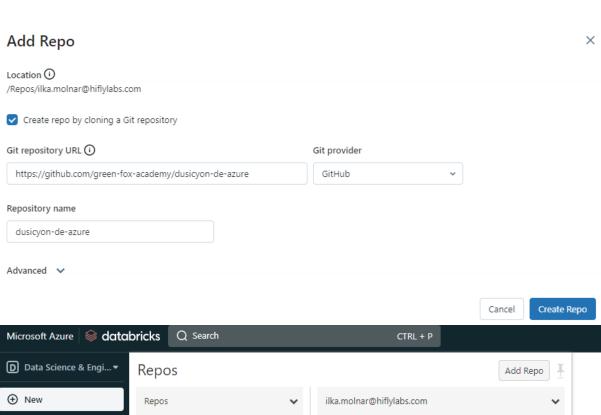






#### · add repo





ilka.molnar@hiflylabs.com

■ Workspace

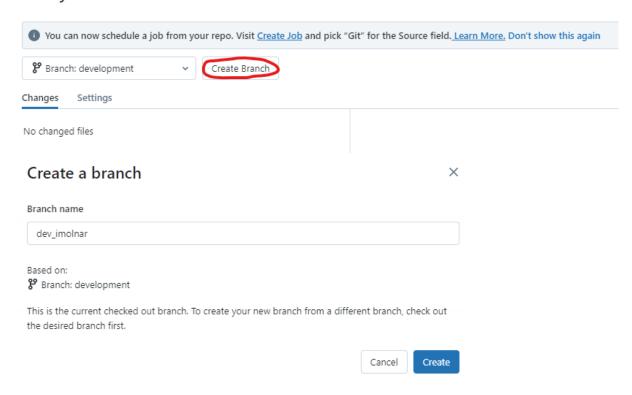
🕼 dusicyon-de-azure

₽ master



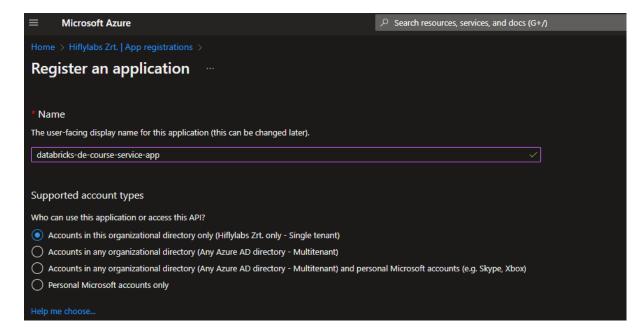
create your feature branch

#### dusicyon-de-azure



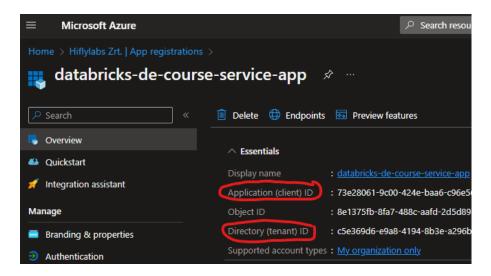
## 5.3.2 Storage account mounting

Register an Azure AD application (Azure Active Directory/App registrations/New registration)

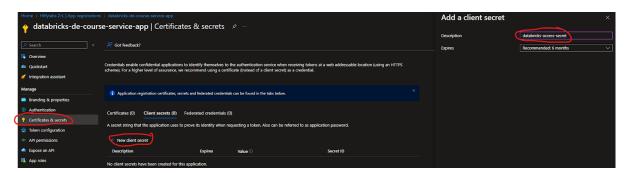




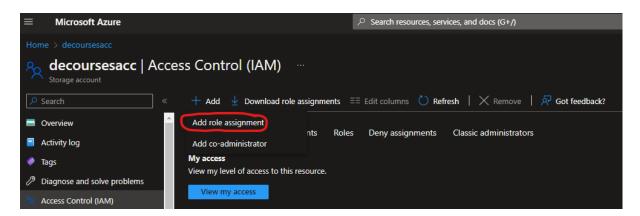
copy the client id and the tenant id to notepad



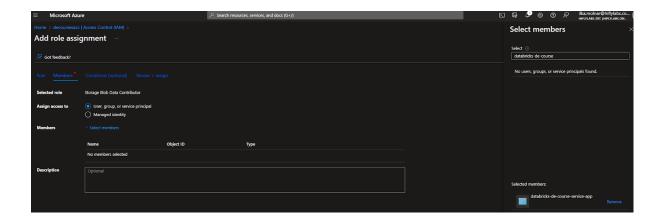
· generate an authentication key (new client secret) and copy the value to notepad



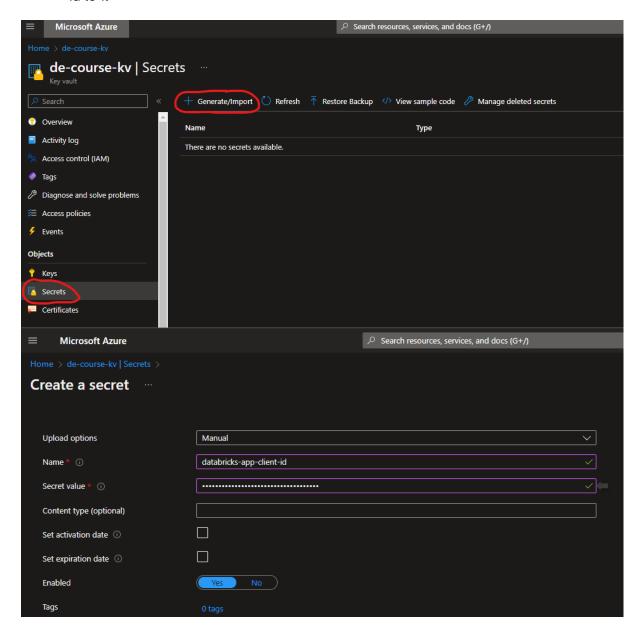
• Grant service principal access to ADLS account (grant storage blob data contributor role to your databricks service principal on your storage account)



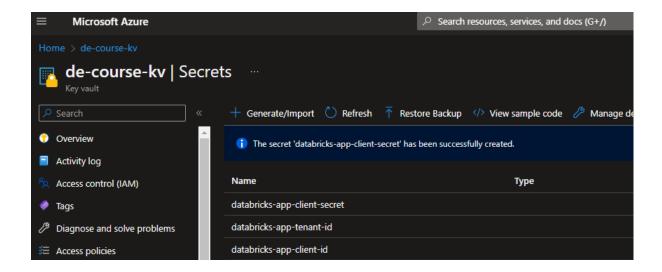




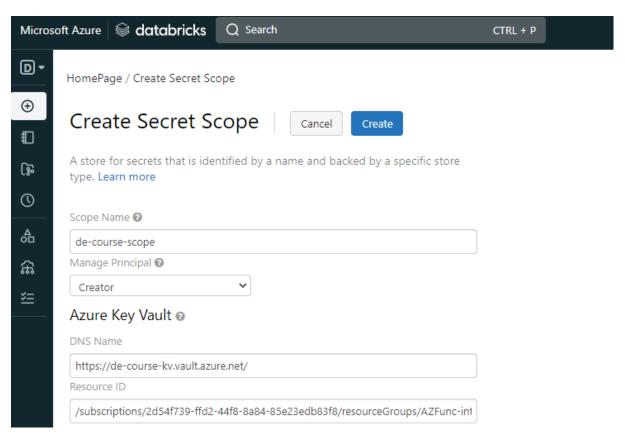
 Create an Azure Key Vault and add the application secret, the client id and the tenant id to it



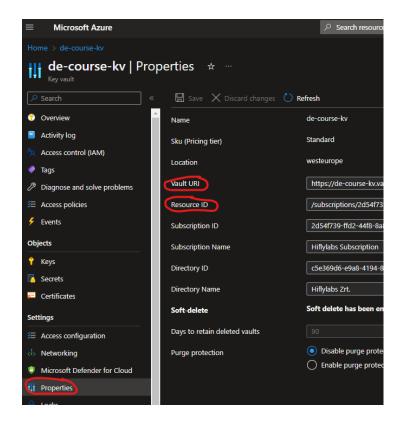




 Create an Azure Key Vault-backed Secret Scope in Azure Databricks (go to https://<DATABRICKS-INSTANCE>#secrets/createScope and replace
 CDATABRICKS-INSTANCE> with your actual Databricks instance URL)







· Mount ADLS to Databricks using Secret Scope

