**Autodesk (Technical Problem #1):** In the world of CAD design, well-established best practices guide the creation of intricate models. However, the process of ***material selection*** introduces complexities that can lead to potential design revisions and time wastage. Material selection presents a real-world conundrum, as *multiple viable solutions* often exist for a single shape. The ultimate challenge lies in developing a ***tool*** that provides rational *suggestions*, empowering designers to make informed choices in their creative processes.

This hackathon takes on a crucial mission: to ***train an algorithm*** using ***CAD models*** sourced from the ***Fusion Gallery*** (or a dataset of your choosing) to ***identify suitable materials based on CAD geometries***, thereby expediting the design-to-make cycle. Teams will be tasked with presenting and testing their solutions against ten with ten assemblies with defined ground truths. We invite all participants to join us in this pioneering endeavor, aiming to address the intricacies of material selection in CAD design.

**Problem Statement Breakdown:**

1. **Objective**: To develop a tool (or algorithm) that can *suggest suitable materials* for a given CAD design. The goal is to help designers choose the right material efficiently and avoid unnecessary design revisions.

2. **Data Source**: *Fusion Gallery* (or any other dataset you choose) will provide CAD models, which will be the foundation for your training data.

3. **Evaluation**: Your solution will be tested against *ten assemblies* with predefined ground truths (i.e., correct answers).

**Approach & Preparation:**

**1. Understanding *Material Properties***: Before you can match a CAD design to a material, you need to understand the typical properties of materials (e.g., strength, ductility, conductivity, thermal properties, cost) and how they relate to specific designs or functionalities.

**2. Data Collection & Preprocessing**:

- From the *Fusion Gallery*, source CAD models and their associated materials (if available). This will be your primary dataset.

- *Define features* from these CAD models that the algorithm can understand and relate to material properties. Features could include *volume, surface area, complexity, presence of cavities*, etc.

**3. Machine Learning Model:**

- **Feature Extraction**: Extract features from your CAD models that might influence material choice. This might require some domain knowledge.

- **Training**: Use a *suitable ML algorithm* (like Decision Trees, Random Forests, Neural Networks) to train your model to predict the best material based on the features of a CAD model.

- **Validation & Testing**: Regularly validate your model's performance using a part of your dataset reserved for this purpose.

**4. User Interface**:

- Develop an intuitive UI where designers can upload a CAD model, and the tool will provide material suggestions.

- It's essential to not only suggest a material but also *provide rational reasoning* or *metrics* to show why that material is suitable. This way, designers can trust and understand the recommendation.

**5. Feedback Loop:**

- Allow users to provide feedback on the material suggestions. This feedback can then be used to further refine and train the algorithm.

**Necessary Skills:**

**1. Domain Knowledge in Materials Science**: Basic understanding of material properties and how they correlate with design requirements.

**2. Data Preprocessing & Analysis**: Ability to work with datasets, clean them, and extract meaningful features.

**3. Machine Learning**: Familiarity with ML algorithms and tools, possibly frameworks like TensorFlow, PyTorch, or scikit-learn.

**4. CAD Software Proficiency**: Knowledge in CAD software, possibly Fusion 360 or similar, to understand and process CAD models.

**5. Programming**: Strong proficiency in programming, likely Python, given its extensive libraries for machine learning and data processing.

**6. UI/UX Design**: If you aim to create a tool with a user interface, skills in UI/UX design will be beneficial. Familiarity with web development frameworks or software development platforms will help.

**Planning**:

**1. Data Collection & Feature Extraction**: Dedicate initial days to data collection and understanding. Extract features from CAD models that can influence material choice.

**2. Model Development:** Allocate time for model choice, training, validation, and refinement.

**3. Tool Development**: Parallelly, start working on the tool or interface where the model will be integrated

**4. Testing:** Before the end of the hackathon, test the solution against the provided ten assemblies. Adjust and refine based on results.

**5. Presentation**: Prepare a comprehensive presentation showcasing your approach, challenges faced, your solution, and its benefits.

**Analysis of the JSON file**:

1. **tree**: This might represent the hierarchical structure of the assembly.
2. **root**: This could refer to the root or primary component of the assembly.
3. **occurrences**: These might be instances or occurrences of parts/components within the assembly.
4. **components**: These are likely the individual parts or components that make up the assembly.
5. **bodies**: These might be individual geometric bodies that make up the components.
6. **contacts**: This could represent contact points or areas between different components or bodies.
7. **holes**: This might refer to any holes or openings in the components.
8. **properties**: These are likely physical properties or characteristics of the components or bodies.

For **bodies**:

* The keys seem to be unique identifiers (UUIDs) for each body.

For **properties**:

* The keys include potentially useful features for our task, such as:
  + **name**
  + **bounding\_box**
  + **vertex\_count**
  + **edge\_count**
  + **face\_count**
  + **loop\_count**
  + **shell\_count**
  + **body\_count**
  + **area**
  + **volume**
  + **density**
  + **mass**
  + **center\_of\_mass**
  + **principal\_axes**
  + **xyz\_moments\_of\_inertia**
  + **surface\_types**
  + **vertex\_valence**
  + **design\_type**
  + **likes\_count**
  + **comments\_count**
  + **views\_count**
  + **products**
  + **categories**
  + **industries**

**For a sample body (UUID: bbdf29da-060c-11ec-a52a-02ef91e90f5f):**

* **name**: 'Bolt M6-1'
* **type**: Represents the type of the body, which is 'BRepBody' in this case.
* Various file formats representing the body, such as 'png', 'smt', 'step', and 'obj'.
* **physical\_properties**: Contains properties like 'center\_of\_mass', 'area', and 'volume'.
* **material\_category**: This is our target variable for the ML model - 'Metal\_Ferrous\_Steel' for this body.

**From the sample properties:**

* **name**: 'Untitled'
* **bounding\_box**: Provides the max and min points in 3D space that define the bounding box.
* **area**, **volume**, **density**, and **mass**: Physical properties of the body.
* **design\_type**: Describes the design type of the part or assembly.

**Summary of the Feature extraction:**

* **Part-Level Features**: These are specific to each part/body in the assembly.
  + **uuid**: Unique identifier for the body.
  + **name**: Name of the body.
  + **type**: Type of the body, eg. BRepBody
  + **center\_of\_mass\_x**, **center\_of\_mass\_y**, **center\_of\_mass\_z**: Coordinates of the center of mass.
  + **body\_area**: Area of the body.
  + **body\_volume**: Volume of the body.
  + **material\_category**: Material category (our target variable).
* **Global (Assembly-Level) Features**: These are repeated for each part/body as they pertain to the entire assembly.
  + **assembly\_volume**: Volume of the whole assembly.
  + **assembly\_mass**: Mass of the whole assembly.
  + **assembly\_density**: Density of the assembly.
  + **assembly\_design\_type**: Design type of the assembly.
  + **assembly\_industries**: Industries related to the assembly.