Project 4 on Fuzzy system

Subject: Fuzzy Rule Base

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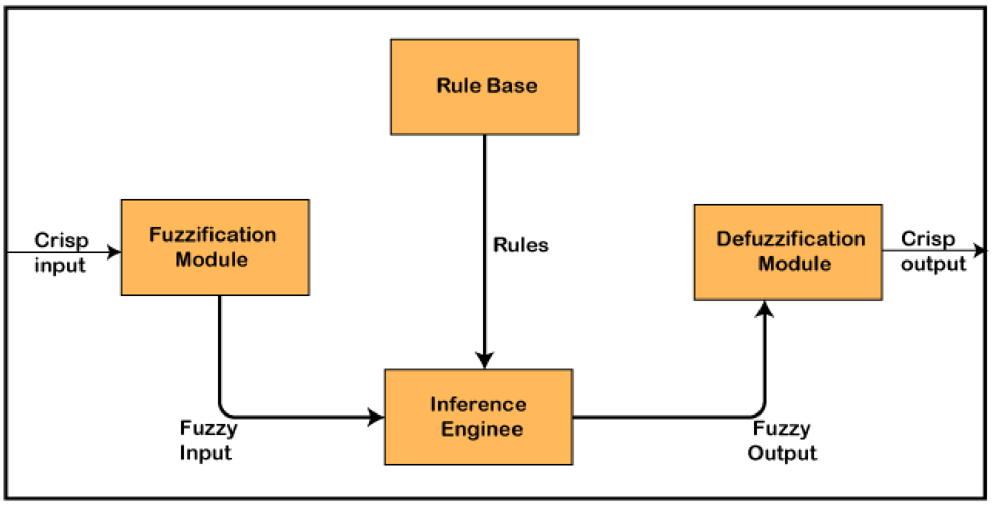


In [1]:

```
import numpy as np
from fcmeans import FCM
from sklearn.metrics import f1_score, precision_score
from copy import deepcopy
import matplotlib.pyplot as plt
import skfuzzy as fuzz
from my_io import read_dataset_to_X_and_y
np.random.seed(4)
```

Build Class to easily have all the variables

I like to have my variable all together so I build a class and named it UniSet(short form of universal set)

Read dataset with my function on my_io module that can shuffle sample and correct missing values also normalized the feature.

In here I shuffle data and use class-mean for the missing values then normalized it with the scaling method into range [0.1, 1] (all values $\in [0.1, 1]$)

I use all the features(12) and change sex from m, f to 0, 1 (actually I map each string to a specific number in my_io module)

In [2]:
```python
class UniSet():
    def __init__(self, file, range_feature, range_label,
                 normalization='scaling', min_value=0.1, max_value=1,
                 shuffle=False, about_nan='class_mean'):
        np.random.seed(1)
        sample, label = read_dataset_to_X_and_y(
            file, range_feature, range_label, normalization, min_value,
            max_value, shuffle=shuffle, about_nan=about_nan)
        self.min_value = min_value
        self.max_value = max_value
        self.universal = sample.astype(float)
        self.label = label
        self.number_of_feature = sample.shape[1]
        self.size_of_universal = sample.shape[0]
        self.diffrent_label = np.unique(label)
        self.number_of_diffrent_label = self.diffrent_label.shape[0]


uni_total = UniSet(
    'dataset/hcvdat0.csv', (2, 14), (1, 2),
    normalization='scaling', shuffle=True, about_nan='class_mean')


print(f'The whole dataset is {uni_total.universal.shape} matrix')
```

```
The whole dataset is (615, 12) matrix
```

> ### Details
>
> In my_io module I have a function named read_dataset_to_X_and_y that get dataset file, range of attributes that are our features, range of attributes that are our labels, normalization which is our normalization method, shuffle which if be True our samples be shuffled, and about_nan that can be "delete" which delete samples with NA values or "class_mean" which replace NA values with mean of that feature in the sample class
>
> Also as I mentioned above this function can get string attributes too by mapping each string to a specific value so now our labels $\in [0, 4]$
>
> I change NA value with class-mean because It doesn't change the similarity(or distance) of two samples in one class
>
> In my class, I have all things that I'll need such as universal (sample data), their label, number of features, size of universal (dataset), different labels (unique labels), and number of different labels.
>
> Our labels in this dataset is attributed [1, 2) and features are attributed [2, 14) (12 features)

Split the whole dataset to Train and Test

As I shuffle the dataset before, now I just consider the first 80% of the data for the train and the rest for the test case

In [3]:

```
def split_train_test(universe: UniSet, train_size: float) -> list[UniSet]:
    train = deepcopy(universe)
    test = deepcopy(universe)
    train.size_of_universal = \
        int(universe.size_of_universal*train_size)
    train.universal = \
        universe.universal[0:train.size_of_universal]
    train.label = \
        universe.label[0:train.size_of_universal]
    test.size_of_universal = (
        universe.size_of_universal - train.size_of_universal)
    test.universal = \
        universe.universal[train.size_of_universal:]
    test.label = \
        universe.label[train.size_of_universal:]

    return train, test


uni_train, uni_test = split_train_test(uni_total, 0.8)
print(f'The train dataset is {uni_train.universal.shape} matrix')
print(f'The test dataset is {uni_test.universal.shape} matrix')
```

```
The train dataset is (492, 12) matrix
The test dataset is (123, 12) matrix
```

> ### Details
>
> I create two classes for train and test by copying the total set and just changing universal, level, and size of universal for both train and test

Create a class for our rule-based system

It contains all variables for our system

In [4]:

```
class RuleBase():
    def __init__(self, number_of_feature: int, min_feature, max_feature):
        self.number_of_feature = number_of_feature
        self.feature_range = np.arange(min_feature, max_feature + 0.01, 0.01)
        self.min_feature = min_feature
        self.max_feature = max_feature
        self.mid_feature = (max_feature + min_feature) / 2
        self.width = None
        self.membership = {'low': None, 'med': None, 'high': None}
        self.rules = []
        self.number_of_rule = None


rule_base = RuleBase(
    uni_train.number_of_feature,
    uni_total.min_value, uni_train.max_value)
```

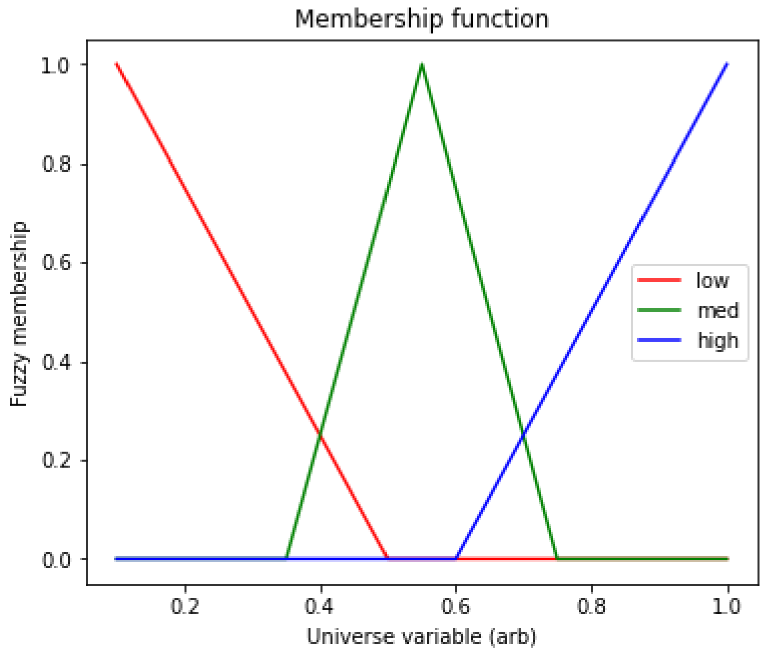
> ### Details
>
> Such as the minimum and maximum values of features (remember that all features are normalized between [min, max]), the width of words, membership functions for each word, rules, and the number of rules

Design membership function for low, medium, and high on feature range for linguistic variables

I decided to create three sets on all features('low', 'med', 'high')

In [5]:

```
def create_linguistic_variables(
        rule_base: RuleBase, width: int = 0.4,
        plot: bool = False, save: bool = False):
    rule_base.width = width

    rule_base.membership['low'] = fuzz.trimf(
        rule_base.feature_range,
        [rule_base.min_feature, rule_base.min_feature,
            rule_base.min_feature + width])

    rule_base.membership['med'] = fuzz.trimf(
        rule_base.feature_range,
        [rule_base.mid_feature - width/2, rule_base.mid_feature,
            rule_base.mid_feature + width/2])

    rule_base.membership['high'] = fuzz.trimf(
        rule_base.feature_range,
        [rule_base.max_feature - width, rule_base.max_feature,
            rule_base.max_feature])

    if(plot is True or save is True):
        plt.figure(figsize=(6, 5))
        plt.plot(
            rule_base.feature_range, rule_base.membership['low'],
            'r', label='low')

        plt.plot(
            rule_base.feature_range, rule_base.membership['med'],
            'g', label='med')

        plt.plot(
            rule_base.feature_range, rule_base.membership['high'],
            'b', label='high')
        plt.ylabel('Fuzzy membership')
        plt.xlabel('Universe variable (arb)')
        plt.title('Membership function')
        plt.legend()
        if(save):
            plt.savefig('report/Membership-function.png')
        if(plot):
            plt.show()


create_linguistic_variables(rule_base, 0.4, True)
```



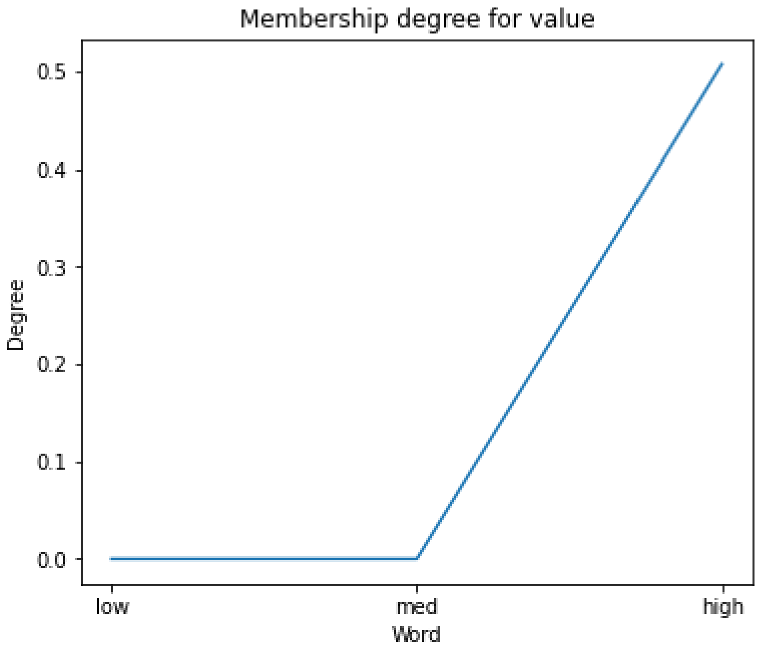
> **Details**
>
> I have normalized all of my features between 0.1 and 1.0

Fuzzify a value

It gets a value and returns a linguistic variable based on our fuzzy-set

In [6]:

```
def fuzzify_value(value: float, rule_base: RuleBase, plot: bool = False):
    degrees = []
    for word in rule_base.membership:
        degrees.append((fuzz.interp_membership(
            rule_base.feature_range, rule_base.membership[word], value), word))
    max_degree = np.argmax(list(list(zip(*degrees))[0]))
    if(plot is True):
        plt.figure(figsize=(6, 5))
        plt.plot(['low', 'med', 'high'], list(list(zip(*degrees))[0]))
        plt.ylabel('Degree')
        plt.xlabel('Word')
        plt.title('Membership degree for value')
        plt.show()
    return degrees[max_degree]

random_value = np.random.rand()
degree, word = fuzzify_value(random_value, rule_base, True)
print(f'Word for {random_value} is {word} with degree {degree}')
```




```
Word for 0.8031633421141696 is high with degree 0.5079083552854241
```

> ### Details
>
> This will find the maximum degree of membership for all of our fuzzy-sets for linguistic variables and return the word with the highest degree.

Fuzzification

It gets a sample with float-values for each feature and fuzzified it and return a sample with linguistic-values

In [7]:

```
def fuzzification(sample: np.ndarray, rule_base: RuleBase):
    fuzzy_sample = []
    for i in range(rule_base.number_of_feature):
        fuzzy_sample.append(fuzzify_value(sample[i], rule_base)[1])
    return np.array(fuzzy_sample)

random_sample = uni_train.universal[
    np.random.randint(uni_train.size_of_universal)]
fuzzy_random_sample = fuzzification(random_sample, rule_base)
print(
    f'Random sample\t{np.round(random_sample, 2)}\n',
    f'Fuzzified sample {fuzzy_random_sample}')
```

```
Random sample	[0.83 0.1  0.44 0.25 0.17 0.15 0.13 0.67 0.54 0.16 0.14 0.64]
 Fuzzified sample ['high' 'low' 'med' 'low' 'low' 'low' 'low' 'med' 'med' 'low'
'low' 'med']
```

> ### Details
>
> we'll find a fuzzified value for each feture of our sample

Find rule

Initially, the idea was to choose each sample as a rule, but as the number of rules grows, I use the fuzzy-c-mean algorithm to cluster similar samples in the class and pick centroids and fuzzify them to get rules in each class.

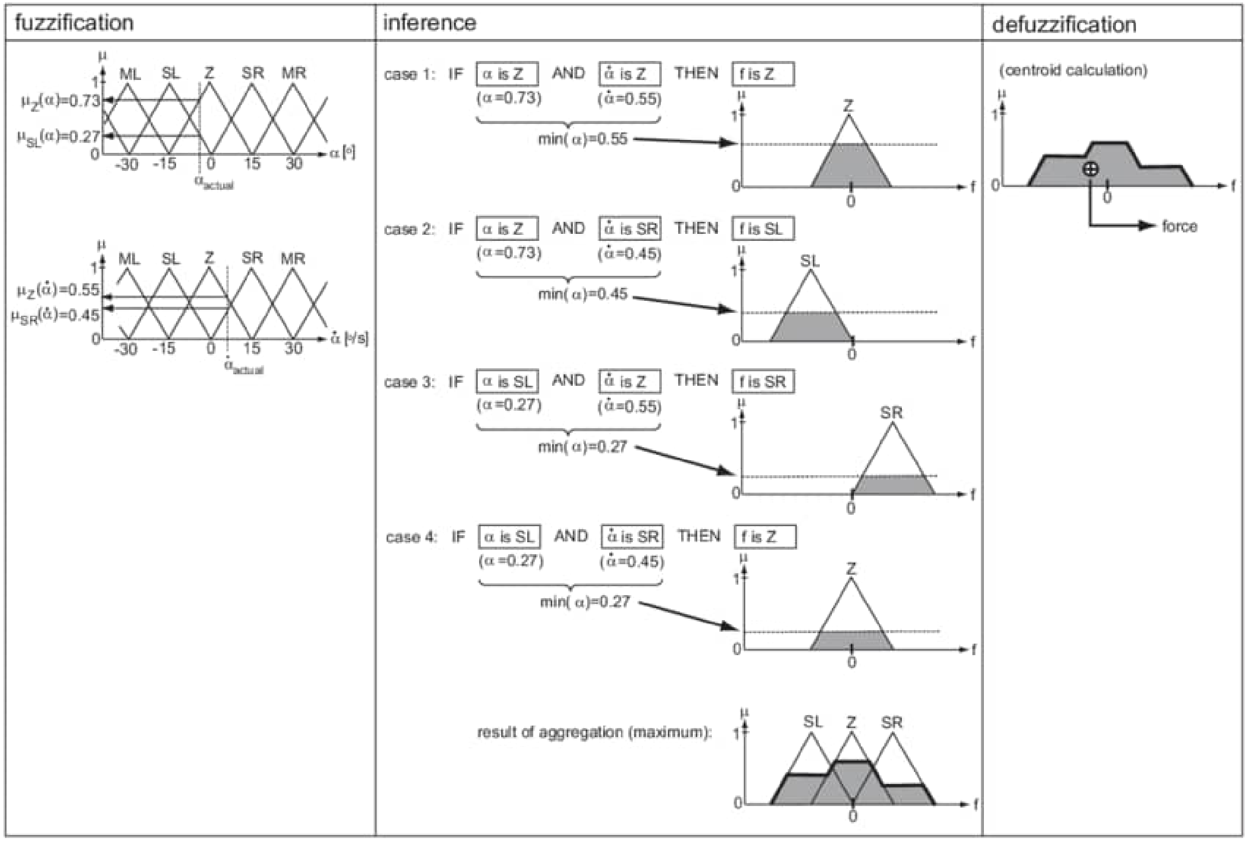
In [8]:

```
def find_rule(uni: UniSet, rule_base: RuleBase, cluster_size: int):
    for label in uni.diffrent_label:
        class_label = uni.universal[(uni.label == label).flatten()]
        size_class_i = class_label.shape[0]
        number_of_cluster = np.ceil(size_class_i / cluster_size)
        f_cmean = FCM(n_clusters=number_of_cluster)
        f_cmean.fit(class_label)
        centers = f_cmean.centers
        for rule in centers:
            rule_fuzzy = fuzzification(rule, rule_base)
            rule_fuzzy = np.hstack([rule_fuzzy, label])
            rule_base.rules.append(rule_fuzzy)
    rule_base.rules = np.array(rule_base.rules)
    rule_base.number_of_rule = rule_base.rules.shape[0]


find_rule(uni_train, rule_base, 20)
print(f'The fuzzy rules is {rule_base.rules.shape} matrix')
```

```
The fuzzy rules is (27, 13) matrix
```

> ### Details
>
> In each rule, there are 13 values, the first 12 of which are features, and the last one is the label

Find class



Fuzzification: In order to find the firing level for each rule, fuzzify the sample (find membership degree for each feature) and then find the minimum(t-norm) of those for finding the firing level of a rule

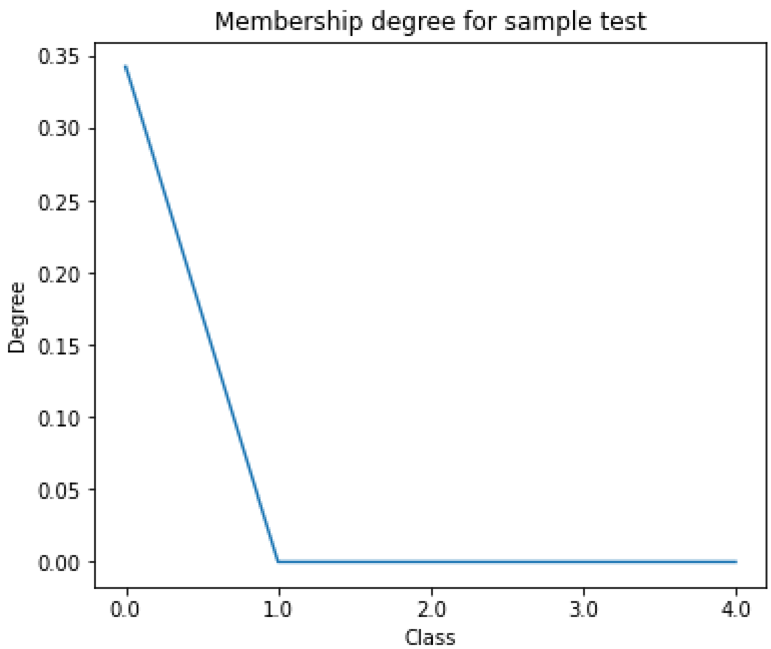
Inference: Then get maximum(t-norm) from all the firing rule

Defuzzification: At the end in order to find the label, find arg-max

In [9]:

```
def find_class(
        sample: np.ndarray, rule_base: RuleBase, plot: bool = False):
    firing_level_class = np.zeros(np.unique(rule_base.rules[:, -1]).shape[0])
    for rule in rule_base.rules:
        #  Fuzzification
        membership_feature = []
        for i in range(rule_base.number_of_feature):
            value_sample = sample[i]
            word_rule_i = rule[i]
            membership_feature.append(
                fuzz.interp_membership(
                    rule_base.feature_range, rule_base.membership[word_rule_i],
                    value_sample))
        firing_level = np.min(membership_feature)

        #  Inference
        firing_level_class[int(float(rule[-1]))] = max(
            firing_level_class[int(float(rule[-1]))], firing_level
        )
    if(plot is True):
        plt.figure(figsize=(6, 5))
        plt.plot(np.unique(rule_base.rules[:, -1]), firing_level_class)
        plt.ylabel('Degree')
```

```
            plt.xlabel('Class')
            plt.title('Membership degree for sample test')
            plt.show()

    #  Defuzzification
    most_degrees = np.argwhere(
        firing_level_class == np.amax(firing_level_class)).reshape(-1)
    return float(np.random.choice(most_degrees))


random_sample = uni_test.universal[
    np.random.randint(uni_test.size_of_universal)]
class_sample = find_class(random_sample, rule_base, True)
print(f'class of random sample {np.round(random_sample, 2)} is {class_sample}')
```




```
class of random sample [0.32 0.1  0.49 0.19 0.19 0.13 0.14 0.46 0.55 0.18 0.14
0.68] is 0.0
```

> ### Details
>
> In cases where the maximum degree isn't unique, I randomly choose one as a label

Predict

For testing our model, in the begining I split data to train and test and biuld the model from train data, now it's time to test our model with test data

In [10]:

```
def predict(samples: np.ndarray, rule_base: RuleBase):
    number_of_sample = samples.shape[0]
    prediced_label = []
    for i in range(number_of_sample):
        sample = uni_test.universal[i]
        prediced_label.append(find_class(sample, rule_base))
    return np.array(prediced_label).reshape((-1, 1))
```

```
predict_label = predict(uni_test.universal, rule_base)
```

In [11]:

```
f1_score = f1_score(uni_test.label, predict_label, average='micro')

print(
    'f1-score of predicted labels on test data is',
    np.round(f1_score, 2))

precision_score = precision_score(
    uni_test.label, predict_label, average='micro')

print(
    'precision-score of predicted labels on test data is',
    np.round(precision_score, 2))
```

```
f1-score of predicted labels on test data is 0.41
precision-score of predicted labels on test data is 0.41
```

Thank you very much for taking the time to read this