

CLASSICAL MODELS FOR MACHINE LEARNING

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TALK OUTLINE

Machine Learning as a Process

Syntax, Semantics, Model

General Model

Semantic Model

Machine Learning as Generalization

Descriptive Model

General Model revisited

Descriptive Language, Satisfaction and Truth

Future Directions:

Topological Models for Machine Learning:

Building topological Syntax and Semantics

INTRODUCTION

Machine Learning - **ML** - is a **process** that includes the following phases:

creating the **target data**,

data **preprocessing**,

learning proper,

patterns **evaluation**,

knowledge presentation

INTRODUCTION

Syntax

Syntax, or **syntactical concepts** refer to simple relations among **symbols** and **expressions** of formal, **symbolic languages**

The expressions of **formal languages**, even if created with a specific meaning in mind, **do not** carry themselves any **meaning**

The meaning is being **assigned** to them by establishing a proper **semantics**

INTRODUCTION

Semantics

Semantics for a given symbolic language \mathcal{L} **assigns** a specific **interpretation** in some domain to all **symbols** and **expressions** of the language

It also involves **related ideas** such as **truth** and **model**
They are called **semantical concepts** to distinguish them from the **syntactical concepts**

INTRODUCTION

Model

The word **model** is used in many situations and has many **meanings** but they all reflect some parts, if not all, of its following **formal** meaning

A structure M is a **model** for a set \mathcal{E}_0 of expressions of the formal language \mathcal{L} if every expression $E \in \mathcal{E}_0$ is **true** in M

INTRODUCTION

We present here three **abstract models** for **ML**:
Semantic, Descriptive and **General**

All of them are abstract **structures** that allow us to
formalize main properties of the **ML Process**

We want **to stress** that they **do not cover** all of the **Machine Learning** field **nor** of all of its existing **algorithms** and **methods**

General Model: Syntax and Semantics for ML

The models we consider are defined in order to address **formally** the

semantics-syntax duality inherent to the

Machine Learning Process

We usually **view** **Machine Learning** results and

present them to the **user** in their **descriptive**,

i.e. **syntactic form** which is the most natural form of

communication

But the **ML process** is deeply **semantical** in its nature

We hence build the **General Model** on two levels:

syntactic and **semantic**

General Model: Syntax and Semantics for ML

The **syntactic level** is represented by a **Descriptive Model**

The **semantic level** is described by the **Semantic Model**

The **semantics-syntax duality** of the **ML process** is expressed in the **General Model** by the **satisfiability** relation

General Model: Syntax and Semantics for ML

We also use the **General Model** to provide a formal **definition** of the **ML process** as a process of **information generalization**

In the model the **data preprocessing** and **learning algorithms** are defined as certain **operators** that act on data

Data are represented in a form of **Knowledge Systems** that have **granularity** associated with them

The **operators** change, or not, their **granularity**

General Model: Syntax and Semantics for ML

General Model is a system

$$\mathbf{GM} = (\mathbf{SM}, \mathbf{DM}, \models)$$

where

\mathbf{SM} is a **Semantic Model**;

\mathbf{DM} is a **Descriptive Model**;

$\models \subseteq \mathcal{P}(U) \times \mathcal{E}$ is called a **satisfaction relation**,

U is the **universe** of \mathbf{SM} ,

\mathcal{E} is the set of **descriptions** defined by the \mathbf{DM}

Semantic Model

Semantic Model is the **most important** component of the **General Model**

When we perform a **learning algorithm** the first **step** is to remove the **key attribute**

This step allows us to **introduce similarities** in the database as now records do not have their unique identification

The **input** into the **learning algorithm** is hence a data table obtained from the **target data** by removal of the key attribute

We call it a **target data table**.

Semantic Model

Machine Learning, as it is commonly said, is a process of **generalization**

In order to model this process we have first to define what does it mean from **semantical** point of view that one stage of the process is **more general** then the other

The idea behind is very simple

It is the same as saying that a formula for example

$$(a + b)^2 = a^2 + 2ab + b^2$$

is **more general** then the formula

$$(2 + 3)^2 = 2^2 + 2 \cdot 2 \cdot 3 + 3^2$$

From **semantical** point of view it means that **ML process** consists of putting objects (records) in **sets of objects**

Semantic Model

From **syntactical** point of view the **ML process** consists of building **descriptions** in terms of pairs **(attribute, values of attribute)** of these **sets of objects**, with some extra **parameters**, if needed

To model this idea we **generalize** Pawlak's model of **Information System**

$$I = (U, A, V_A, f)$$

where $U \neq \emptyset$ is called a set of **objects**;

$A \neq \emptyset, V_A \neq \emptyset$ are called the set of **attributes** and **values of attributes**, respectively;

$f: U \times A \rightarrow V_A$ is called an **information** function

Knowledge System

Knowledge System based on an Information System

$I = (U, A, V_A, f)$ is a system

$K = (K(U), A, E, V_A, V_E, g)$

where $K(U) \subseteq \mathcal{P}(U)$;

E is a finite set of **knowledge attributes** (k-attributes) such that $A \cap E = \emptyset$;

V_E is a finite set of **values of k- attributes**;

g is a partial function called a **knowledge function** (k-function);

$g : \mathcal{P} \times (A \cup E) \rightarrow (V_A \cup V_E)$ is such that:

$g \upharpoonright (\bigcup_{x \in U} \{x\} \times A) = f$;

$\forall S \in \mathcal{P}, \forall a \in A ((S, a) \in \text{dom}(g) \Rightarrow g(S, a) \in V_A)$;

$\forall S \in \mathcal{P}, \forall e \in E ((S, e) \in \text{dom}(g) \Rightarrow g(S, e) \in V_E)$

Semantic Model

We view **ML algorithms** as certain **operators** and define the model as follows

Semantic Model is a system

$$SM = (\mathcal{P}(U), \mathcal{K}, \mathcal{G})$$

where

$U \neq \emptyset$ is the **universe**;

$\mathcal{K} \neq \emptyset$ is a set of knowledge systems, called **learning process states**;

$\mathcal{G} \neq \emptyset$ is the set of **operators**;

Each operator $p \in \mathcal{G}$ is a partial function on the set of all ML process states, i.e.

$$p : \mathcal{K} \longrightarrow \mathcal{K}$$

Semantic Model; ML Operators

Machine Learning Operators

In machine learning the **preprocessing** and **ML proper** stages are inclusive/exclusive **categories**

The **preprocessing** is an integral and very important stage of the **ML process** and needs as careful **analysis** and the **ML proper** stage

We distinguish **two** disjoint classes of **operators**:

the **preprocessing** operators \mathcal{G}_{prep} and

machine **learning proper** operators \mathcal{G}_{ml}

We put

$$\mathcal{G} = \mathcal{G}_{prep} \cup \mathcal{G}_{ml}$$

Semantic Model; ML Operators

Machine Learning Operators

The main **idea** behind the concept of an **ML operator** is to capture not only the fact that ML techniques **generalize** the data but also to **categorize** existing methods and algorithms

We want to make sure that our categorization **distinguishes**, as it should, for example **clustering** from **classification** , or from **association analysis**

Semantic Model; ML Operators

Machine Learning Operators

We want make sure that all **classification** algorithms fall into one category defined by **classification operators** and

all **clustering** algorithms would fall into a category defined by **clustering operators**

The third category we consider is the **association** analysis described in our framework by **association operators**

Semantic Model; ML Operators

We don't include in our analysis purely statistical methods like regression and others

This gives us only three classes of operators to consider:

classification operators \mathcal{G}_{class}

clustering operators \mathcal{G}_{clust}

association operators \mathcal{G}_{assoc}

Semantic Model; ML Operators

We prove the following

Theorem

Let \mathcal{G}_{class} , \mathcal{G}_{clust} and \mathcal{G}_{assoc} be the sets of all classification, clustering, and association operators, respectively

The following conditions hold

- (1) $\mathcal{G}_{class} \neq \mathcal{G}_{clust} \neq \mathcal{G}_{assoc}$
- (2) $\mathcal{G}_{clust} \cap \mathcal{G}_{class} = \emptyset$
- (3) $\mathcal{G}_{assoc} \cap \mathcal{G}_{clust} = \emptyset$

Machine Learning Process

We model here **preprocessing** and **learning proper** stages of **learning process** and adopt the following definition

Definition

Any sequence K_1, K_2, \dots, K_n ($n \geq 1$) of learning states is called a **data preprocessing** process, if there is a preprocessing operator $G \in \mathcal{G}_{prep}$, such that

$$G(K_i) = K_{i+1}, \quad i = 1, 2, \dots, n-1$$

The sequence K_1, K_2, \dots, K_n is called a **learning proper** process if there is a learning operator $G \in \mathcal{G}_{ml}$, such that

$$G(K_i) = K_{i+1}, \quad i = 1, 2, \dots, n-1$$

Descriptive Model

Given a Semantic Model $SM = (\mathcal{P}(U), \mathcal{K}, \mathcal{G})$

We associate with it its **descriptive counterpart** and we define it as follows

Descriptive Model is a system

$$DM = (\mathcal{L}, \mathcal{E}, DK)$$

where:

$\mathcal{L} = (\mathcal{A}, \mathcal{E})$ is called a descriptive **language**;

\mathcal{A} is a countably infinite set called an **alphabet**;

$\mathcal{E} \neq \emptyset$ and $\mathcal{E} \subseteq \mathcal{A}^*$ is the set of **expressions** of \mathcal{L} ;

$DK \neq \emptyset$ and $DK \subseteq \mathcal{P}(\mathcal{E})$ is a set of **descriptions** of knowledge states

Descriptive Model

As in a case of **semantic model**, we build the **descriptive model** for a given application

We assume however, that whatever is the application, the **descriptions** are always build in terms of **attributes** and **attributes values**, some logical **connectives**, and some **parameters**, if needed

For example, a whole **neural network** with its nodes and weights can be seen as a formal **description** and the **knowledge states** could represent changes in **parameters** during the **training**

Descriptive Learning

When we build here a model for a **descriptive learning** we assume that the **descriptions** are build from **attributes** and **attributes values** and two logical connectives: **conjunction** and **implication**

We use them to model different kind of **rules** that are being **learned** by **descriptive ML** algorithms:

discriminant and **characteristic** rules in **classification analysis**;

association rules in **association analysis**;

or other rules obtained by hybrid systems

General Model Revisited: Satisfaction and Truth

General Model is a system

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U is the **universe** of **SM**,

\mathcal{E} is the set of **descriptions** defined by the **DM**

All the components of **GM** except the **satisfaction relation** have already been defined

General Model Revisited: Satisfaction and Truth

As the last step we define the **satisfaction relation** \models and the notion of **truth** in **GM** as follows

Satisfaction Definition

For any $S \in \mathcal{P}(U)$ and for any $F \in \mathcal{E}$,

$$S \models F \text{ if and only if } \exists K \in \mathcal{K}(S \models_K F)$$

Truth Definition

We define $F \in \mathcal{E}$ is **true** (we write it symbolically $\models F$) in **GM** as follows

$$\models F \text{ if and only if } \exists K \in \mathcal{K}(\models_K F)$$

FUTURE DIRECTIONS

Topological Models for Machine Learning

Building **Topological Machine Learning** Syntax and Semantics