Norm Conflict Identification using Deep Learning

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Introduction

- Norms have a central role in society as they regulate expected behaviors from human interactions.
- A common way to formalize sets of norms applied to agreements between individuals is through contracts.
- To define regulations in contracts, norms use the deontic constructs of permission, prohibition, and obligation.

Introduction

- However, depending on how norms are declared, they may conflict between each other
  - Detecting such conflicts is not trivial within formal languages
  - Much recent work on norm conflict detection and resolution
- As real contracts tend to be long and complex, detecting deontic conflicts is a non-trivial task for humans
  - Problem compounded by ambiguities in natural language
- In this work we detect norm conflicts in contracts using a deep learning algorithm to (semi) automate this task

Background

Two key background elements to this work

- Formal definitions of normative conflicts
- Deep learning applied to natural language

Norm Conflicts

- We use two conflict causes to base our norm conflict identification
  - **1st cause**: When the same act is subject to different types of norms.
    1. Company X must pay product Z taxes.
    2. Company X may pay product Z taxes.
  - **2nd cause**: When one norm requires an act, while another norm requires or permits a 'contrary' act.
    1. Company X shall deliver product Z on location W at time T.
    2. Company X must deliver product Z on location Q at time T.
- Key to detecting **potential** conflicts in natural language is **semantic similarity**

Convolutional Neural Networks

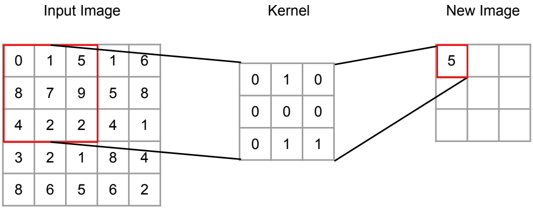
- Deep neural networks (DNNs) can be described as artificial neural networks with a “large” number of hidden layers
- Its depth allows networks to extract complex relations from data, which results in more accurate classification
- The most common DNNs are: convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders

Convolutional Neural Networks

- CNNs were first introduced by LeCun *et al.*
- They use convolutional layers to extract features from the input
  - Using a series of kernels (filters), they create new representations from the input
  - Each kernel consists of a set of weights used for sequential multiplication of input pixels
- To gradually reduce the dimensions of the layers on the forward pass, CNNs employ pooling layers after convolution layers
  - This layer reduces the dimension by using a kernel that "pools" information from areas of the image into one pixel
  - A common pooling layer is max pooling, which pools the largest number from the filter selection

Convolutional Neural Networks

- **Convolution layer**



Input Image

0	1	5	1	6
8	7	9	5	8
4	2	2	4	1
3	2	1	8	4
8	6	5	6	2

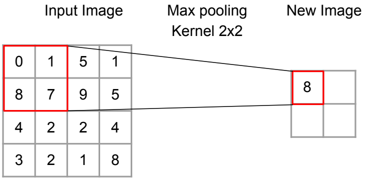
Kernel

0	1	0
0	0	0
0	1	1

New Image

5		

- **Pooling layer**



Input Image

0	1	5	1
8	7	9	5
4	2	2	4
3	2	1	8

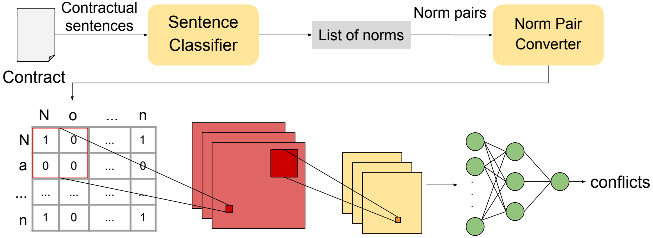
Max pooling
Kernel 2x2

New Image

8	

Bringing it all together

- Our approach is divided into two steps:
  - Norm Identification; and
  - Pairwise Norm Conflict Identification



	N	o	...	n
N	1	0	...	1
a	0	0	...	0
...	...	...	...	...
n	1	0	...	1

Norm Identification

- To identify norms in contracts, we train a support vector machine (SVM) classifier using manually-labeled contract sentences.
- Features of the SVM consist of a bag of words representation of the original sentences
- We define sentences as being either *norm* or *non-norm*, resulting in a set of 699 norm sentences and 494 non-norm sentences from a total of 22 contracts.
- As result, our classifier is able to receive a sentence as input and return whether it is a norm or not.

Conflict Identification: Norm Pair Representation

- We need a representation for norm pairs suitable for use as input to CNNs
- We want to identify conflicts and they often occur with similar norms (same party and norm action), thus
    - we build a matrix representation to compute character-level similarity between two norm sentences.

Norm Pair Representation

- The characters of one norm represent the columns and the characters of the other represent the lines, as illustrated below.
- If the character in line i is the same of the character in column j, we assign 1 to the position i, j, otherwise, we assign 0.

Norm2

Norm 1

	n	o	· · ·	r	m	z
n	1	0	· · ·	0	0	0
o	0	1	· · ·	0	0	0
	⋮	⋮	· · ·	⋮	⋮	⋮
r	0	0	· · ·	1	0	0
m	0	0	· · ·	0	1	0
w	0	0	· · ·	0	0	0

LeNet CNN Architecture

- To process norm pairs in our matrix representation, we use the LeNet architecture from LeCun *et al.*
- This architecture is a CNN with two convolutional layers followed by a fully-connected layer.
- We rely on the convolutional layers of CNNs to extract useful features from data in order to identify conflicts between norm pairs.

Experiments

We conducted independent tests for each phase of our approach

- Norm identification
- Conflict identification

Results for Norm Identification

- To train and test our classifiers, we use a set of manually annotated sentences dividing it into 80% for training and 20% for testing.
- The SVM classifier yields 90% accuracy and 91% f-measure

Results for Norm Conflict Identification

- To evaluate the norm conflict identifier, we used a 10-fold cross-validation step dividing our dataset into training, validation, and test.
- To prevent overfitting, we use the early stopping technique
- Training performed using a Tesla K40 GPU over six epochs, taking around 5 minutes per epoch.

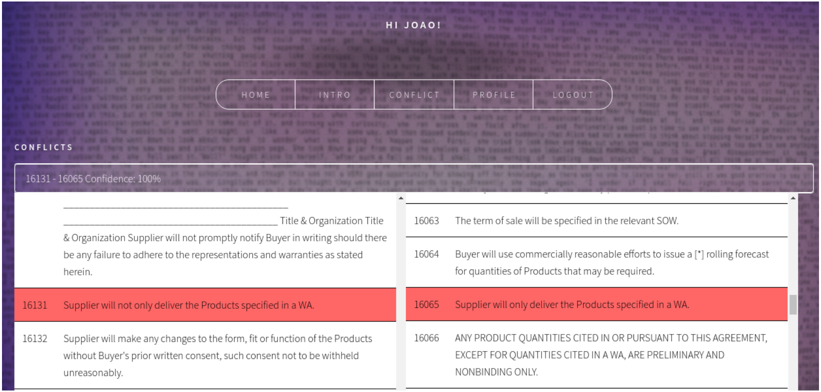
Fold	0	1	2	3	4	5	6	7	8	9	**Mean**
Accuracy	0.85	0.85	0.76	0.95	0.85	0.76	0.71	0.95	0.95	0.80	0.84

Conclusion

- We developed a two-phase approach to identify potential conflicts between norms in contracts.
  - an SVM sentence classifier to identify norms among common sentences; and
  - a CNN to identify conflicts in norm pairs
- As future work, we aim to:
  1. Train other types of DNNs, including RNNs such as long short-term memory (LSTM)
  2. Use SyntaxNet to extract syntactic trees from norms and then use it as features to detect conflicts involving temporal and conditional definitions
  3. Substantially increase our annotated dataset using community-supplied data
- We acknowledge Google for its Latin America Research Award, which partly funded João Paulo and Felipe

Demo

You can help us improve the future of this research through our web tool!



CONFLICTS

16131 - 16065 Confidence: 100%

	____ ____ Title & Organization Title & Organization Supplier will not promptly notify Buyer in writing should there be any failure to adhere to the representations and warranties as stated herein.
16131	Supplier will not only deliver the Products specified in a WA.
16132	Supplier will make any changes to the form, fit or function of the Products without Buyer's prior written consent, such consent not to be withheld unreasonably.

16063	The term of sale will be specified in the relevant SOW.
16064	Buyer will use commercially reasonable efforts to issue a [*] rolling forecast for quantities of Products that may be required.
16065	Supplier will only deliver the Products specified in a WA.
16066	ANY PRODUCT QUANTITIES CITED IN OR PURSUANT TO THIS AGREEMENT, EXCEPT FOR QUANTITIES CITED IN A WA, ARE PRELIMINARY AND NONBINDING ONLY.

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