

Automate TRIZ solving process

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Introduction

Context

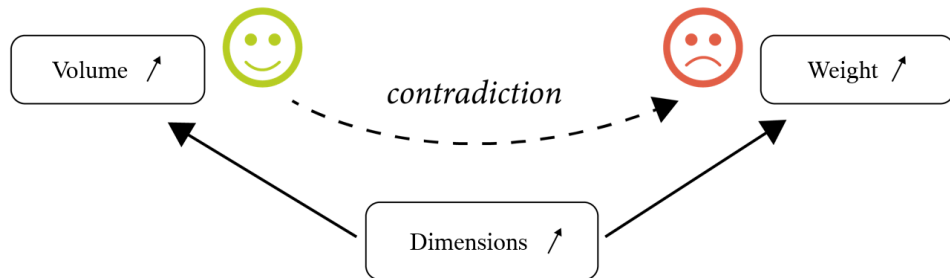
- ▶ TRIZ theory : 1946, Guenrich Altshuller
⇒ How to optimize the problem solving process
- ▶ Adapt solutions from other domains
- ▶ How to compare problems from different domains?
⇒ **Contradiction**



FIGURE – Guenrich Altshuller

Introduction

Contradiction



Introduction

Evaluation and action parameters

- ▶ **Action Parameter (AP)** : with respect to which the designer has a power of modification of state. This type of parameter generally has two opposite directions that can potentially bring a benefit to the object.
- ▶ **Evaluation Parameter (EP)** : whose nature lies in the ability to evaluate the positive and negative aspect resulting from a choice of the designer. This type of parameter has only one logical direction of progress, the other direction seems aberrant.

Introduction

Patents and TRIZ matrix

[illegible]

Introduction

Patents and TRIZ matrix

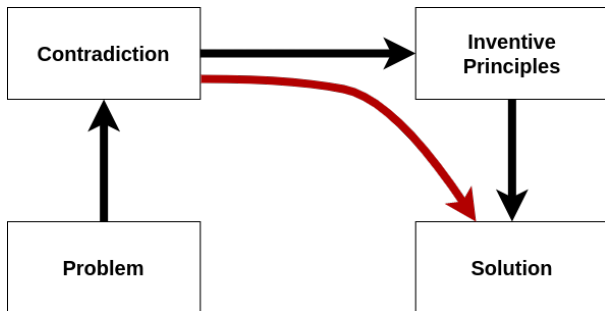
Feature Improving Feature	Weight of moving object	Weight of stationary object	Length of moving object	Length of stationary object	Area of moving object	Area of stationary object	Volume of moving object	Volume of stationary object	Speed	Force (Intensity)	Stress or pressure	Shape
	1	2	3	4	5	6	7	8	9	10	11	12
Weight of moving object	+	-	15, 8, 29, 34	-	29, 17, 38, 34	-	29, 2, 40, 28	-	2, 8, 15, 38	8, 10, 18, 37	10, 36, 37, 40	10, 14, 35, 40
Weight of stationary object	-	+	-	10, 1, 29, 35	-	35, 30, 13, 2	-	5, 35, 14, 2	-	8, 10, 19, 35	13, 29, 10, 18	13, 10, 29, 14
Length of moving object	8, 15, 29, 34	-	+	-	15, 17, 4	-	7, 17, 4, 35	-	13, 4, 8	17, 10, 4	1, 8, 35	1, 8, 10, 29
Length of stationary object	-	35, 28, 40, 29	-	+	-	17, 7, 10, 40	-	35, 8, 2, 14	-	28, 10	1, 14, 35	13, 14, 15, 7
Area of moving object	2, 17, 29, 4	-	14, 15, 18, 4	-	+	-	7, 14, 17, 4	-	29, 30, 4, 34	19, 30, 35, 2	10, 15, 36, 28	5, 34, 29, 4
Area of stationary object	-	30, 2, 14, 18	-	26, 7, 9, 39	-	+	-	-	-	1, 18, 35, 36	10, 15, 36, 37	-
Volume of moving object	2, 26, 29, 40	-	1, 7, 4, 35	-	1, 7, 4, 17	-	+	-	29, 4, 38, 34	15, 35, 36, 37	6, 35, 36, 37	1, 15, 29, 4

1. Segmentation
2. Extraction, Separation, Removal, Segregation
3. Local Quality
4. Asymmetry
5. Combining, Integration, Merging
6. Universality, Multi-functionality
7. Nesting
8. Counterweight, Levitation
9. Preliminary anti-action, Prior counteraction
10. Prior action
11. Cushion in advance, compensate before
12. Equipotentiality, remove stress
13. Inversion, The other way around
14. Spheroidality, Curvilinearity
15. Dynamicity, Optimization
16. Partial or excessive action
17. Moving to a new dimension
18. Mechanical vibration/oscillation
19. Periodic action
20. Continuity of a useful action
21. Rushing through
22. Convert harm into benefit, "Blessing in disguise"
23. Feedback
24. Mediator, intermediary

Introduction

Limitations of traditional inventive solving process and TRIZ matrix

- ▶ A shortcut in the problem solving process



Introduction

Objectives : Contradiction Identification, Solution generation

► 2 Objectives :

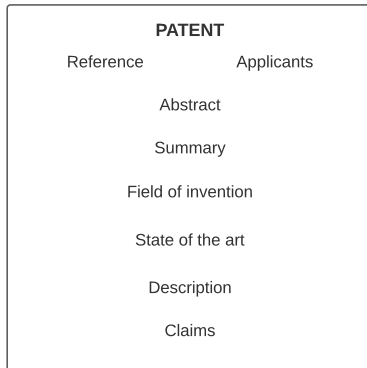
⇒ **Domain scanning, contradiction identification**

⇒ **Provide solutions**

Objectives

Domain scanning, contradiction identification

- ▶ **Understand inventions** (in patents) to help **identify core contradictions** and **domain trends**
- ▶ **Extract solved contradictions**
 - ⇒ know what problems the patent can solve
 - ⇒ deep understanding of the solution
- ▶ **Application : mapping of a domain** (in early stage of a research project)

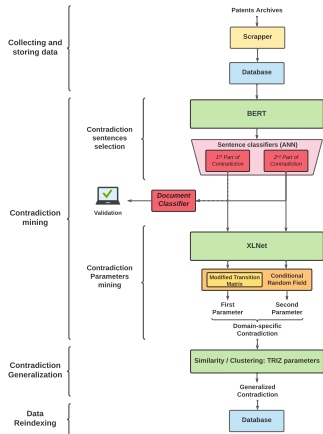


Objectives

Exploiting patents' data to provide solutions

► 5 steps strategy :

- ⇒ Collecting and storing Data
- ⇒ Contradiction mining
- ⇒ Contradiction Generalization
- ⇒ Re-indexing Data
- ⇒ Solution DB +
Solution Generation Model



Objectives

Select appropriate data for users

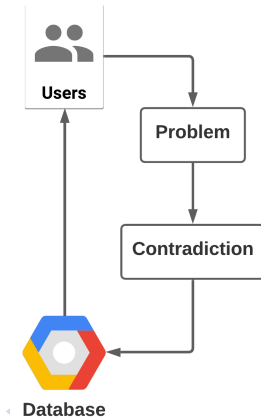
► How it works :

- ⇒ User formulates contradiction
- ⇒ Contradiction request is sent to the database
- ⇒ Results patents ranked by domain

► Advantages :

- ⇒ Instantaneous response (search engine)
- ⇒ Results are classified by domain (choice between inventivity and state of the art)
- ⇒ Selection of high value data with possible and fast post-processing

► Drawback : Lots of results, hard to rank



Objectives

Generate solutions

► How it works :

⇒ Reuse solution database from 2.1. and add inventive principles

⇒ Generate a solution from following equation :

context + contradiction + inventive principle = solution

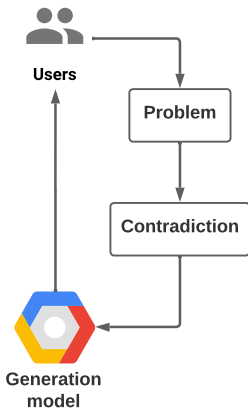
⇒ Train the generative model on the database to learn how to apply inventive principles

► Advantages :

⇒ Instantaneous

⇒ One solution per chosen inventive principle

⇒ No need to rank



Introduction

Contradiction extraction

- ▶ Where to find the **solved contradiction** in a patent ?
- ▶ Contradictions in **prior art** are **solved contradictions**
- ▶ Example of scenario :
 - "The traditional method is disadvantageous for this reason :... (1st parameter)"
 - "To solve this problem, an approach has been proposed by..."
 - "Nevertheless, it (2nd parameter)"

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Preamble

Patents analysis, contradiction retrieval

- ▶ TF-IDF (Term Frequency-Inverse Document Frequency), LDA (Latent Dirichlet Allocation) clustering (Korobkin et al. [2017] Liang and Tan [2007])
- ▶ Keywords and key-sentences (Chang et al. [2017])
- ▶ **No successful approach** to extract contradictions from patents

State of the art

Extractive summarization

- ▶ Choice of the extraction method : **Summarization**
- ▶ **Extractive** summarization (Nallapati et al. [2017])
Abstractive summarization (Zhang et al. [2019])
- ▶ Contradiction = Parameters
- ▶ Parameters may not be explicitly quoted
 - ⇒ **Sentences selection** is more appropriate -> "Extractive"
 - ⇒ 2 class - **Classification** (first part/second part)

State of the art

Extractive summarization

- ▶ Naive bayesian approaches (Kupiec et al. [1995], Aone et al. [1997])
- ▶ Hidden Markov models (Conroy and O'leary [2001])
- ▶ Conditional Random Field-based models (Shen et al. [2007])
- ▶ LSTMs : SummaRuNNer(Nallapati et al. [2017]) and NeuSum(Zhou et al. [2018])
- ▶ Pretrained encoders : BERT(Devlin et al. [2019]), XLNet(Yang et al. [2019])
- ▶ Best performance on extractive summarization : **BERT+classifier**

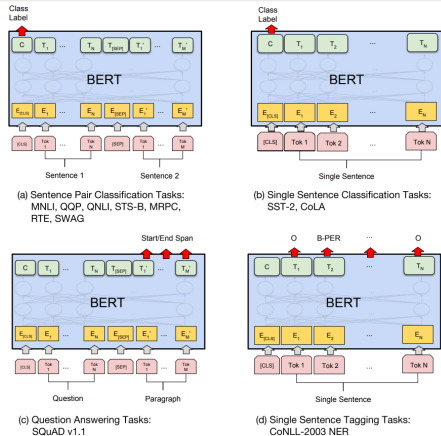
Summarization model

BERT encoder

► **BERT**(Google) Devlin et al. [2019]

► **Contextual** representations

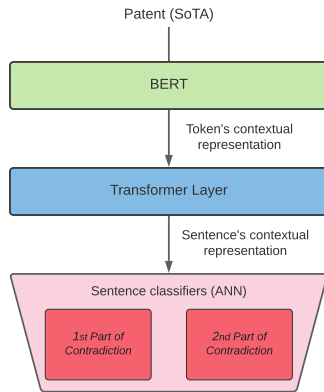
► 12 stacked encoders with **attention mechanism**



SummaTRIZ : Summarization Networks for Mining Patent Contradiction

ICMLA2020

- ▶ Sentence representation computation through additional **Transformer Layer**
- ▶ 2 classifiers
- ▶ **2-classes classification**



Dataset

Dataset and training

- ▶ Patents from **United States Patent and Trademark Office** (USPTO)
- ▶ **New** CSIP dataset of 1600 patents with contradiction + 1600 patents without contradiction)
- ▶ **Human experts** labeling (20000 patents)
- ▶ 1 contradiction per patent / all similar sentences are extracted

Dataset : example

Dataset and training

This invention relates to a stroller, and more particularly to a wheel assembly for a stroller, which includes a single wheel. 2. Referring to 1 and 2, a conventional stroller 1 is shown to include a stroller frame 10 with four legs 101, two front wheel assemblies 11 mounted respectively to two of the legs 101, and two rear wheel assemblies 12 mounted respectively to the other two of the legs 101. 2 is a bottom view of one of the front wheel assemblies 11. Each of the front wheel assemblies 11 includes two front wheels 13, a wheel seat 14 disposed between the front wheels 12, and a wheel axle 15 extending through the front wheels 13 and the wheel seat 14. Each of the wheel seats 14 has a leg-connecting portion 141 sleeved rotatably on a respective one of the legs 101, and an axle-connecting portion 142, within which the wheel axle 15 is journaled. To enhance the comfort of the baby carried on the stroller 1, a vibration-absorbing device not shown can be disposed within the axle-connecting portion 142 of each of the wheel seats 14. When it is desired to push the stroller 1 to advance along a straight path, a forward force A is applied to the stroller frame 10. In each of the front wheel assemblies 11, since the forward force A is located midway between two frictional forces B that are generated between the ground and the front wheels 13 and since the direction of the forward force A is parallel to those of the frictional forces B, the stroller 1 can advance along a straight path 16. When the stroller 1 moves over a lawn or uneven road surfaces, it is necessary for the stroller wheels to have a large diameter so as to ensure the comfort of the baby. However, if each of the front wheel assemblies 11 has two large-diameter front wheels 13, the total volume and weight of the stroller 1 will increase significantly so that it is difficult to push the stroller 1.

Training

Dataset and training

- ▶ Contradiction extraction = difficult task
 - ⇒ Dataset is **not big enough to learn from scratch** (transformer layer)
 - ⇒ Transfer Learning
- ▶ 1st extractive summarization training on **newspapers** (CNN/DailyMail dataset)
- ▶ **Model fine-tuning** with the 1600 labeled patents

Limitations

Dataset and training

- ▶ Ranking of sentences but no **validation mechanism** for an extraction
- ▶ Millions of **unlabeled patents** are available and not exploited

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Extraction validation

Document classification

- ▶ Purpose : provide a mechanism to **eliminate patents "without" contradictions**
- ▶ Possible inputs : classification outputs, sentence representations
- ▶ 3 possible **architectures** (MLP, LSTM, Transformer)

Generative Adversarial Network (Goodfellow et al. [2014])

GAN and semi-supervised learning

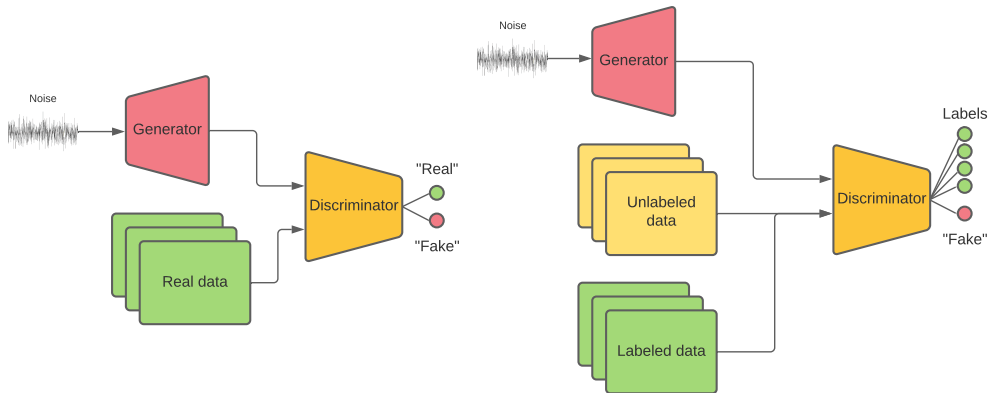
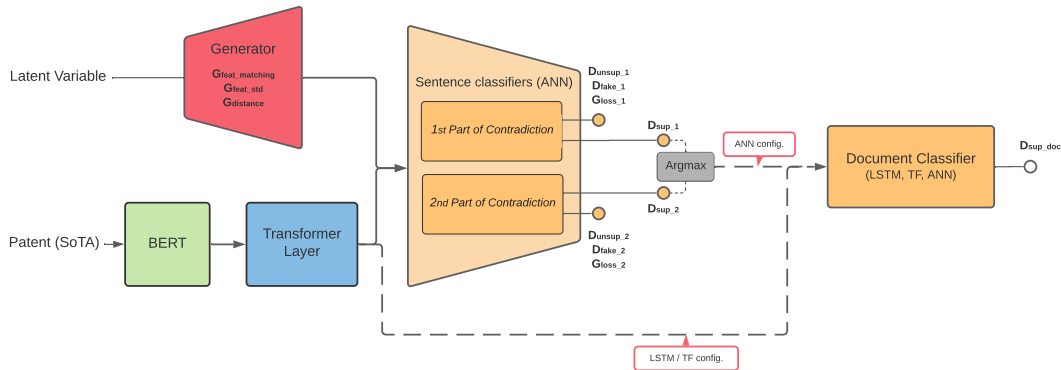


FIGURE – Original GAN and semi-supervised GAN

PaGAN : Generative Adversarial Network for Patent understanding

ICDM2021



Generative Adversarial Network

GAN and semi-supervised learning

- ▶ Sentence-level losses :

$$D_{sup} \quad i = E_{x,y \sim p_{data}}[-\log(P(\hat{y}_{s_i} = y_{s_i} | x, y_{s_i} \in (C, \overline{C})))] \quad (1)$$

$$D_{unsup} \quad i = E_{x \sim p_{data}}[-\log(P(\hat{y}_{s_i} = y_{s_i} | x, y_{s_i} = \bar{F}))] \quad (2)$$

$$D_{fake} \quad i = E_{z \sim p_z}[-\log(P(\hat{y}_{s_i} = y_{s_i} | x, y_{s_i} = F))] \quad (3)$$

- Document-level loss :

$$D_{sup \ doc} = E_{x, y \sim p_{data}}[-\log(P(\hat{y}_d = y_d | x, y_d \in (Dc, \overline{Dc})))] \quad (4)$$

Generative Adversarial Network

GAN and semi-supervised learning

- ▶ Generator's sentence-level loss :

$$G_{loss} = \sum_{i=1}^2 E_{z \sim p_z} [-\log(1 - P(\hat{y}_{s_i} = y_{s_i} | x, y_{s_i} = F))] \quad (5)$$

- ▶ Generator's matching losses :

$$G_{feat_mean} = E_{x \sim p_{data}(x)} f(x) - E_{z \sim p_z(z)} f(G(z)) \quad (6)$$

$$G_{feat_std} = \sigma_{x \sim p_{data}(x)} f(x) - \sigma_{z \sim p_z(z)} f(G(z)) \quad (7)$$

- ▶ To avoid mode collapse :

$$Cos_{similarity}(A, B) = \frac{A \cdot B}{\|A\| \|B\|} \forall A, B \in \mathbb{R}^n \quad (8)$$

Sentence classification (1st part)

Results

Model	Loss	TP	FP	TN	FN	Accuracy	Precision	Recall	F1 score	S	S _m
SummaTRIZ _D	0.140	0	0	61959	2276	0.96	0	0	0	548	1158
SummaTRIZ _{TL}	0.115	576	510	61449	1700	0.97	0.53	0.25	0.34	1119	1711
Baseline _{ANN_D}	0.140	0	1	65248	2276	0.97	0	0	0	535	1149
Baseline _{ANN_{TL}}	0.115	575	482	64767	1701	0.97	0.54	0.25	0.35	1098	1710
PaGAN _{PROB}	0.112	575	457	71584	1701	0.97	0.56	0.25	0.35	1168	1736
PaGAN _{ANN}	0.112	532	414	71689	1744	0.97	0.56	0.23	0.33	1187	1760
PaGAN _{LSTM}	0.112	509	368	71704	1767	0.97	0.58	0.22	0.32	1186	1752
PaGAN _{TF}	0.113	649	592	71438	1627	0.97	0.52	0.29	0.37	1143	1759

TABLE – Sentence classification 1 (with LSTM generator)

Sentence classification (2nd part)

Results

Model	Loss	TP	FP	TN	FN	Accuracy	Precision	Recall	F1 score	S	S _m
SummaTRIZ _D	0.171	0	0	60526	3709	0.94	0	0	0	1750	2692
SummaTRIZ _{TL}	0.129	1814	815	59711	1895	0.96	0.69	0.49	0.57	2493	3127
Baseline _{ANN_D}	0.170	0	0	63816	3709	0.95	0	0	0	1766	2692
Baseline _{ANN_{TL}}	0.129	1849	881	62935	1860	0.96	0.68	0.50	0.57	2500	3131
PaGAN _{PROB}	0.120	2091	936	69672	1618	0.97	0.69	0.56	0.62	2619	3226
PaGAN _{ANN}	0.120	2288	1119	69551	1421	0.97	0.67	0.62	0.64	2626	3206
PaGAN _{LSTM}	0.118	2323	1156	69483	1386	0.97	0.67	0.63	0.65	2645	3213
PaGAN _{TF}	0.121	2327	1228	69369	1382	0.96	0.65	0.63	0.64	2631	3220

TABLE – Sentence classification 2 (with LSTM generator)

Document classification

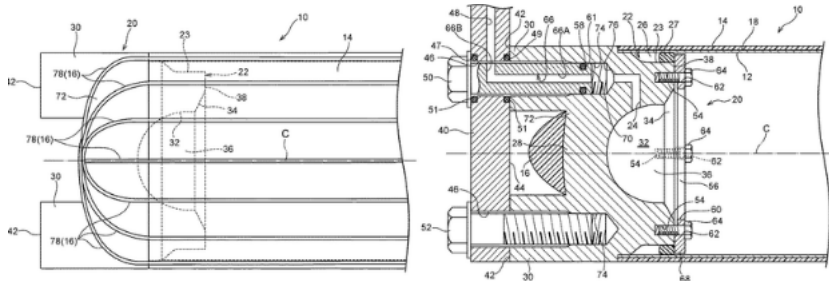
Results

Model	Loss	TP	FP	TN	FN	Acc.	Pre.	Recall	F1 score	CO _{Found}	CO _{valid}
SummaTRIZ _D	-	0	0	1600	1600	0.50	0	0	0	153	0
SummaTRIZ _{TL}	-	386	135	1465	1214	0.58	0.74	0.24	0.36	582	213
Baseline _{ANN_D}	0.529	1274	490	1110	326	0.74	0.72	0.80	0.76	146	96
Baseline _{ANN_{TL}}	0.502	1275	438	1162	325	0.76	0.74	0.80	0.77	580	467
PaGAN _{PROB}	-	335	126	1474	1265	0.57	0.73	0.21	0.33	668	192
PaGAN _{ANN}	0.466	1335	431	1169	265	0.78	0.76	0.83	0.79	666	576
PaGAN _{LSTM}	0.481	1370	507	1093	230	0.77	0.73	0.86	0.79	654	567
PaGAN _{TF}	0.467	1345	427	1173	255	0.79	0.76	0.84	0.80	648	552

TABLE – Document classification (with LSTM generator)

US10619794 B2

Presentation



US10619794 B2

First claim

A pressure vessel : a shell defining an internal cavity ; first and second bosses disposed within the cavity and respectively extending through opposing longitudinal ends of the shell, the first boss defining a longitudinally extending central orifice ; and a reinforcement support disposed within the cavity, secured to the first boss radially outward of the central orifice, extending from the first boss to the second boss, and secured to the second boss, wherein the reinforcement support includes a plurality of reinforcement bars that extend from the first boss to the second boss.

US10619794 B2

Problem/Contradiction extraction

Extract the core problem that the patent aims to solve :

- ▶ This configuration enhances the **rigidity** of the liner, so the high-pressure hydrogen tank can hold high-pressure hydrogen inside.
- ▶ However, because the high-pressure hydrogen tank disclosed in jp-a -94 is a large tank shaped like a barrel, there are cases where the **cabin space and/or luggage space is reduced** to install the high-pressure hydrogen tank in a vehicle.

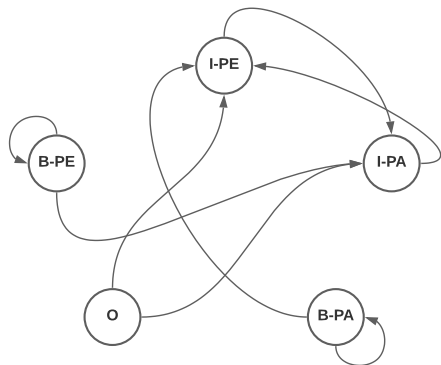
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Parameter mining

Named-Entity Recognition

- ▶ Evaluation parameters (EP) and Action parameters (AP) mining
- ▶ Close to a Named-Entity Recognition (B-I-O scheme)
- ▶ New parameters dataset, USPTO patents
 - ⇒ 1100 patents
 - ⇒ 9000 parameters
- ▶ B-I-O \rightarrow impossible transitions



Example Dataset

INVENTION_TITLE // Orifice sealing physical barrier // REF PATENT // US07010885-20060314 // ABSTRACT // A physical barrier for sealing an orifice in a panel member is presented. The physical barrier includes a carrier that has one or more locating pins mounted on it. The pins are adapted to locate the carrier in the orifice. The physical barrier also includes a sealing material attached to the carrier. Also included is a method of installing the physical barrier into an orifice of a panel member. // STATE_OF_THE_ART //

Physical barriers are commonly used to seal orifices in certain objects, such as panel members in motor vehicles, buildings, household appliances, etc. These barriers normally are used to prevent physical materials, fluids, and gases, such as environmental contaminants, fumes, dirt, dust, moisture, water, etc., from passing through the orifice.

For example, an automotive panel, such as a door panel, typically has several orifices in the sheet metal, which are created for various reasons during manufacturing. Further, various structural components of automobile bodies have a variety of orifices, hollow posts, cavities, passages and openings that can allow contaminants into the passenger compartment.

These holes, orifices, and cavities are typically barricaded with duct tape, butyl-based plastic patches, and sealing plugs made from foam, rubber, or some other material. Another known physical barrier for cavities involves introducing a foam product or a fiberglass matting to fill in the cavity. Known barriers, however, are unsatisfactory for a variety of reasons. Sealing plugs, which were a step forward over other barriers, utilize snap-fit clips to hold the plug in place, i. e., in an orifice of a panel member. However, snap-fit clips on a sealing plug, without more, are insufficient because the clips cannot produce a contaminant-tight seal between the plug and the panel member. To overcome this, a sealer material, such as compressible rubber, adhesive, caulk or mastic, has been used in combination with a carrier to form the sealing plug. The sealer material may create a contaminant-tight seal between the carrier and the panel member. With the introduction of the sealer material, however, new drawbacks arise. Often the sealer material needs to be activated in order to form a contaminant tight seal.

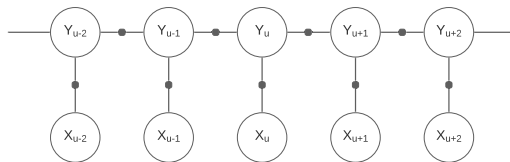
Such activation may be in the form of mixing two components together or physical kneading of the material. This can be labor intensive, as well as placing a time limit on the installation process because the barrier must be placed in the orifice during the relatively limited active period of the sealer material. Furthermore, known sealer materials have not been able to protect against prolonged exposure to contaminants, but only against intermittent exposure to contaminants. This is a particular problem with respect to water. Installation of known snap-fit barriers has also been problematic because installation of such barriers exactly in the center of the orifice has been difficult. Once the barrier is placed askew in the orifice, the presence of the sealer material prevents the barrier from centering itself. For the same reason, it is also difficult for the installer to center the barrier. This skewed or off-center installation of the barrier creates two problems. First, it places unequal strain on the snap-fit clips that hold the barrier in place. This tends to lead to failure of one or more of the clips, which results in a leaky seal. To overcome this type of failure, stiffer snap-fit clips, which require more force to flex, are required. This in turn increases the force needed to install the barrier into the orifice to such a degree that a person cannot perform installation without mechanical assistance. Thus, force-multiplying tools or machines are required to install the barrier. The use of tools or machines to install these barriers increases the complexity and cost of the installation process beyond that which is economical. Second, off-center installation increases the number of failed seals.

Known sealer materials cannot compensate for off-center installation. Off-center installation can lead to gaps between the panel member and the carrier that are not filled by the sealer material. Thus, the size of the barrier must be closely matched to the size of the orifice to ensure that there are no gaps between the carrier and the panel member. Therefore, expensive precision manufacturing techniques are required in the formation of the orifice and the carrier to ensure that the barrier cannot be installed incorrectly, i. e., off-center. Consequently, the inventor hereof has recognized a need for a physical barrier that overcomes one or more of these problems. // CLAIMS // 1. A physical barrier for sealing an orifice in a panel member, comprising: a carrier configured to cover the orifice when installed; a plurality of conically-shaped locating pins having sloped guide surfaces, said locating pins extending from said carrier and configured to extend into the orifice when said carrier is installed so as to maintain said carrier substantially centered over the orifice.

Architecture

Named-Entity Recognition

- ▶ Baseline = Pretrained encoder (BERT, XLNet) + token classifier (MLP)
- ▶ Conditional Random Field to model label sequences
- ▶ Unary Potentials = pretrained encoder
- ▶ Pairwise Potentials = CRF's transition matrix



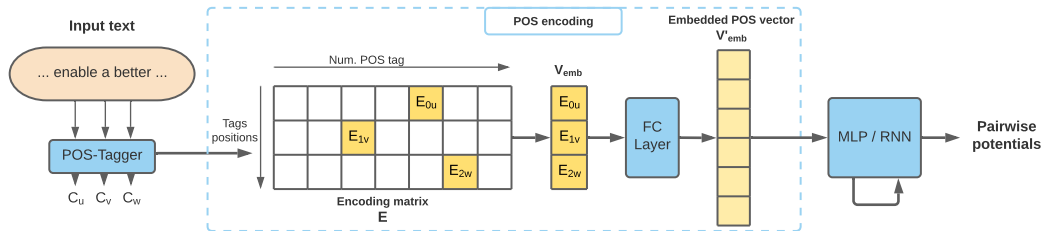
Model's limitations

Named-Entity Recognition

- ▶ Pairwise potentials are constant
 - \Rightarrow TRIZ EP/AP strongly dependent on the syntactic structure
 - \Rightarrow Pairwise potentials should be dependent on the syntactic structure

CRF-pos (ESWA)

Pairwise potentials generation



Results of EP/AP mining

Results

Model	Loss	TP	Prec.	Recall	F1	Support
<i>Baseline</i>						
Devlin et al. (2019)	0.43	3680	31.7	42.4	36.2	8694
<i>Baseline_{CRF}</i>						
Lafferty et al. (2001)	0.393	3870	36.9	44.5	40.3	8694
ParaBERT _{CRF-es}	0.137	3893	47.5	44.8	46.1	8694
ParaBERT [*] _{CRF1}	0.299	3643	32.4	41.9	36.5	8694
ParaBERT [*] _{CRF1-es}	0.141	3867	47.3	44.5	45.9	8694
ParaBERT [*] _{CRF2}	0.293	3568	27.7	41.0	33.1	8694
ParaBERT [*] _{CRF2-es}	0.134	3753	46.6	43.2	44.8	8694
ParaBERT ^{**} _{CRF1}	0.390	4079	46.3	46.9	46.6	8694
ParaBERT ^{**} _{CRF1-es}	0.149	3890	47.4	44.7	46.0	8694
ParaBERT ^{**} _{CRF2}	0.420	4034	46.0	46.4	46.2	8694
ParaBERT ^{**} _{CRF2-es}	0.149	4010	48.6	46.1	47.3	8694

Model	TP _{AP}	Prec _{AP}	Recall _{AP}	F1 _{AP}	Support _{AP}
<i>Baseline</i>					
Devlin et al. (2019)	183	19.3	11.1	13.7	1651
<i>Baseline_{CRF}</i>					
Lafferty et al. (2001)	265	23.5	16.0	18.7	1651
ParaBERT _{CRF-es}	308	43.4	18.7	26.0	1651
ParaBERT [*] _{CRF1}	186	19.1	11.3	14.1	1651
ParaBERT [*] _{CRF1-es}	327	40.1	19.9	26.5	1651
ParaBERT [*] _{CRF2}	193	13.1	11.6	12.1	1651
ParaBERT [*] _{CRF2-es}	266	35.6	16.2	22.2	1651
ParaBERT ^{**} _{CRF1}	393	37.4	23.8	29.0	1651
ParaBERT ^{**} _{CRF1-es}	308	46.5	18.7	26.6	1651
ParaBERT ^{**} _{CRF2}	381	37.8	23.1	28.7	1651
ParaBERT ^{**} _{CRF2-es}	330	43.9	20.0	27.5	1651

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Conclusion

Results

- ▶ Contradiction mining is a step in automatic solving process
- ▶ **2 new datasets** (sentence/parameters)
- ▶ Sentences : 40% contradictions are extracted / FP must be reduced (50%)
- ▶ Solving process with 2 linked approaches (DB, generative model) relying on the contradiction mining model
- ▶ Next steps :
 - ⇒ Release of the solution DB (search engine, Objective 2.1)
 - ⇒ Train generative model (Objective 2.2)
 - ⇒ Multi task model (sentence + parameters)

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