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Deception Detection in criminal analysis: from lie detector to stylometry

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Outline



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Definition

Psychologist define deception in humans as "an act that is intended to foster in another person a belief or understanding which the deceiver considers to be false" (Zuckerman et al., 1981).

To detect deception means to detect the presence of a mental state in a person.

The problem is that we have no direct access to the mental states (Granhag et al., 2015).

Therefore, it is necessary to identify measurable signs, be they physiological or behavioral, associated with the mental state of interest.

The perfect cue of deception would appear if and only if the mental state is present: like the Pinocchio's growing nose. But... does it exists?



Human performance

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• is not better than chance (Bond and De Paulo, 2006).

O'Sullivan and Ekman (2004) found that some people - they call *"wizards"* - are particularly skilled, but Bond and Uysal (2007) analysed their results and concluded that *"chance can explain results that the authors attribute to wizardry"*.

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does not improve even after specific training.

Kassin and Fong (1999) tried to develop lie detection training procedures to be employed in forensic settings, however Levine et al. (2005) claim that this is not particularly effective to improve the ability of subjects.

Cues of deception

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Physiological variables:

Non-Verbal behavior:

Verbal behavior:

Cues of deception

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 - Complex recording tools;
 - High subjects' cooperation;
 - Objective cues' measurement.
- Non-Verbal behavior:

· Verbal behavior:

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- Physiological variables:
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 - Simple to complex recording tools;
 - · Low to high subjects' cooperation;
 - Subjective to objective cues' measurement;
- Verbal behavior

Based on the kind of clues of deception which are examined, in literature there can be found studies focusing on:

 Complex recording tools; · High subjects' cooperation; · Objective cues' measurement. Simple to complex recording tools; Low to high subjects' cooperation; · Subjective to objective cues' measurement; · Simple recording tools; Low subjects' cooperation; · Subjective to objective cues' measurement;

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According to mostly unspoken beliefs, such areas would be characterised as follows:

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According to mostly unspoken beliefs, such areas would be characterised as follows:

 Physiological variables: 	No conscious control.	\odot
 Non-Verbal behavior: 	Partial conscious control;	<u>.</u>
Verbal behavior:	Full conscious control;	

But... Is it true?

Techniques of interview can be associated to every kind of experimental paradigm.

However, when the verbal behavior is the object of analysis, the techniques of interview are themselves the tool of data collection:

 \rightarrow

- Physiological variables
- Non-verbal behavior
- Verbal behavior

- Technical devices + techniques of interview;
- Video/audio recording and/or human observation + techniques of interview;
- Techniques of interview
 + audio recording.

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- Laboratory studies:
 - · Control of the variables;
 - Ground truth known;
 - · Possibility of replication experiments.
 - · Lack of ecological validity;
- Field studies:

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- Laboratory studies:
 - · Control of the variables;
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 - Possibility of replication experiments.
 - Lack of ecological validity;
- Field studies:
 - · No control of variables;
 - Ground truth often unknown;
 - No possibility of replication experiments.
 - Ecological validity.

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ments.	

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The polygraph, better known as Lie Detector, is a device that was realised in 1921 by John Augustus Larson (Britannica, 2003), and records some **bodily** activities:

- Electro-Dermal Activity (EDA);
- Blood pressure;
- Pulse;
- Respiration.



In the United States the debate regarding admissibility in Court and effectiveness of physiological measures for the evaluation of truthfulness in testimonies began on 1923, in the famous case of Frye vs. United States (Saxe and Ben-Shakhar, 1999).

The polygraph does not 'read the mind', but simply measures physiological variables, which are assumed to be associated to deception. This association can be of two different kinds, which lead to two different strategies in the use of polygraph:

- Concern approach;
- Orienting reflex approach.

Assumption Polygraph can be employed to detect signs of stress which are supposed to be related to the production of deceptive statements.

Protocol Control Question Test (CQT), an interview protocol in five phases aimed to check the bodily reactions of the subjects to crime-related and control questions (Reid, 1947; Raskin, 1986).

Performance Field studies showed that 83% to 89% of liars were correctly classified. 53% and 75% of innocent examinees were correctly identified, but a quota from 12% to 47% was misclassified (Vrij, 2008). Pro/Cons High accuracy in detecting liars.

Vulnerability to false-positive errors.

Assumption "An orienting response [...omissis...] occurs when someone is confronted with a personally significant stimulus" (Vrij, 2008).

Protocol Concealed Information Test (CIT) (Verschuere et al., 2011), originally known as Guilty Knowledge Test (GKT), which implies the presentation of stimuli, usually images, the subjects should be familiar with.

Performance In field studies, the protocol achieves 76% to 88% of accuracy in identifying liars.Only 1% to 6% of innocent subjects were incorrectly classified (Vrij, 2008).

Pro/Cons Resistance to false-positive errors. Some weakness with false-negative errors. Applicability limited to specific settings.

Electroencephalographic (EEG) brain event-related potentials (ERPs) can support the application of the GKT protocol.

While the Autonomic Nervous System (ANS) responses take several seconds to manifest, the P300 wave is much faster: its name comes from the typical peak latency of about 300 ms., which can actually be of 500-600 ms. for complex stimuli.

"P300 is sensitive to the rarity and meaningfulness of a stimulus, and the amplitude varies with the strength of recognition memory" (Granhag et al., 2015).



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P300-GKT is 100% accurate in detecting memories stored in the brain.	:
It is not possible to know which memory is crime-related.	
P300 has low spatial and high temporal resolution.	:
P300-GKT is rarely employed in police practice.	

One of the most innovative approaches to deception deception relies on modern techniques of **neuro-imaging**.

The functional Magnetic Resonance Imaging (fMRI) detects activity of the brain areas, measuring changes in:

- Blood flow;
- Oxygen consumption.



The use of fMRI to detect deception represents a fascinating perspective: in the United States some private laboratories already provide services of deception detection based on fMRI technology.



Image from noliemri.com

The use of fMRI to detect deception represents a fascinating perspective: in the United States some private laboratories already provide services of deception detection based on fMRI technology.

However, Cohen (2012) claims that the advertisement of the technology *"violates consumer protection law under the Federal Trade Act."*

In fact, the findings in the scientific literature are not consolidated yet and only concern laboratory studies.



Image from noliemri.com

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Experimental designs are far from realistic scenarios. "Deception detection accuracy in the study with perhaps the most elaborate mock crime scenario used so far (Kozel et al., 2009) was rather low (67%)."(Granhag et al., 2015)

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Ganis et al. (2011) found that, when the subjects were instructed to act countermeasures - mental actions carried out in front of irrelevant stimuli, in order to increase their saliency - the sensitivity (proportion of deceptive cases correctly classified) fell from 100% to 33%.

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fMRI is characterised by high spatial and low temporal resolution.

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Studies focused on non-verbal clues of deception usually rely on the activity of trained raters who watch videos in which liars and true tellers interact, with the aim of analyzing some form of non-verbal behavior.

Coding systems are adopted in order to detect frequency, duration and intensity of several non-verbal cues and to compare the results for liars and true tellers.

Aim of these studies is to detect liars rather than single lies.

Assumptions

As formalised by Zuckerman et al. (1981), clues of deception might be found exploring the following factors:

Emotional reactions. Liars may experience feelings of guilt and fear of being unmasked, which could elicit anxiety signs.

Cognitive effort. Liars have to accomplish several tasks:

- To formulate narratives different from the truth;
- To be plausible and to not fall into contradiction;
- To check the others' reactions.

Liars are supposed to show more hesitations, more speech latencies and to reduce gestures of illustration.

Attempted behavioral control. Liars must be convincing. This task could be difficult, since some bodily reactions are almost beyond the voluntary control.

Discrepancies are expected between verbal and non-verbal behaviors, or different non-verbal behaviors.

The studies of Ekman rely on the idea that strong emotions can activate facial muscles almost automatically.

Two kind of signals which may be issued by the subjects:

Leakage cues. Behavioral expressions that the liars fail to squelch.

Deception cues. They share the same nature of the previous cues, but they are so brief that the emotion which caused them cannot be recognized.



Subjects can suppress their expressions within 1/25 sec, but this lapse of time is enough for a trained observer to detect such micro-expressions (Ekman, 2001).

The work of Ekman is famous, but questioned, especially for the inability to replicate facial coding:

"In brief, [...] the less aware we are of a behaviour, the more likely the behaviour is to signal a lie. Subsequent scientific data have not been supportive of the original leakage theory, and subsequent work by Ekman and his colleagues shifted to focus more on the face and micro-expressions. Even with these modifications, however, leakage theory remains controversial" (Granhag et al., 2015; Weinberger, 2010) In a more recent literature review, Vrij (2008) took into consideration the study of De Paulo et al. (2003) and summarised a set of 132 studies focused on non-verbal cues to deception.

He selected a restricted number of cues, whose the analyses in literature he considered particularly reliable.

They were divided as follows:

- 7 Vocal cues;
- 10 Visual cues.

- Speech hesitations: use of speech fillers e.g., 'ah', 'um', 'er', 'uh' and 'hmmm';
- 2 Speech errors: grammatical errors, word and/or sentence repetition, false starts, sentence change, sentence incompletions, slips of the tongue, etc.;
- Pitch of voice: changes in pitch of voice, such as rise in pitch or fall in pitch;
- 4 Speech rate: number of spoken words in a certain period of time;
- **5** Latency period: period of silence between question and answer;
- 6 Pause durations: length of silent periods during speech;
- **7** Frequency of pauses: frequency of silent periods during speech (Vrij, 2008).

- 1 Gaze: looking into the face of the conversation partner;
- 2 Smile: smiling and laughing;
- 3 Self-adaptors: scratching the head, wrists, etc.;
- Illustrators: hand and arm movements designed to modify and/or supplement what is being said verbally;
- **5** Hand and finger movements: movements of hands or fingers without moving the arms;
- 6 Leg and foot movements: movements of legs and feet;
- 7 Trunk movements: movements of the trunk;
- 8 Head movements: head nods and head shakes;
- 9 Shifting position: movements made to change seating position;
- 10 Blinking: blinking of the eyes (Vrij, 2008).

The effect sizes, evaluated by Vrij (2008), were found significant for only three cues:

• Pitch: liars use a higher pitch of voice than truth tellers, but the effect is small.

Furthermore, the difference between liars and true tellers usually is only few Hertz, and needs professional devices to be detected;

 Illustrators: liars show fewer illustrators than true tellers, with a 'small' effect size;

3 Hand and finger movements: liars move hands and fingers less than true tellers, with a 'small/medium' effect size. However, Vrij et al. (1997) analyzed this variable on 181 subjects, finding that '64% of them showed a decrease in hand/finger movements during deception, whereas 36% showed an increase of these movements during deception'. The overall results "show an erratic pattern and indicate that many conflicting results have been found" (Vrij, 2008):

- In some studies speech hesitations are more frequent in liars than in true tellers, in others they are less frequent.
- The pauses in the speech seem to be longer in liars than in true tellers, but not necessarily more frequent.
- Gaze behavior does not seem to be related to deception, even though as popular opinion is that liars tend to look away from their interlocutor. However this behavior is easy to control and people are aware of its importance for communication, thence it cannot be considered an effective marker for deception (Vrij, 2008).

In spite of the wide set of cues considered by De Paulo et al. (2003), most of them showed non-significant trends.

The outcome of different studies are often inconsistent.

The behavioral cues reveal emotions: they are not specific for deception.

There is evidence that clusters of cues can show patterns of deceit, even though their composition may change in different situations.

"A cue akin to Pinocchio's growing nose does not exist" (Vrij, 2008).

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Verbal behavior Levels of analysis Approaches SVA RM Cognitive interview Reid technique 5 NLP

Stylometry and DD Stylometry and Personality The corpus DeCour Personality evaluation Methods Results Discussion Conclusion Cross-disciplinarity The role of DD Future perspectives Computational linguistics To deal with language means to face two orders of complexity:

Semantics. Semantic analyses are aimed to collect and analyse the information, through the examination of:

- The internal logic of the narrative, that is possible contradictions or discrepancies between statements;
- The external logic, which concerns the relation between statements and objective elements (Smirnov, 1988).
- Stylistics. Stylistic analyses are aimed to evaluate the reliability/truthfulness of the narrative, through the examination of:
 - The linguistic style of the narrative, that is its degree of similarity with stylistic models which supposedly distinguish truthful from deceptive communications.

For the purposes of deception detection, semantic data and stylistic patterns are often jointly evaluated by trained experts.

- Statement Validity Assessment (SVA);
- Reality Monitoring (RM);

In police practices, however, techniques of interview were developed, not necessarily addressing deception detection, but specifically aimed to the collection of information. Different techniques were proposed for two main scenarios, that is the interview of cooperative or uncooperative subjects.

- · Cognitive interview;
- Reid Technique.

In the last 10-15 years, in the field of Natural Language Processing (NLP), new approaches to deception detection arose, relying essentially on the analysis of stylistic features, mostly automatically collected.

Statement Validity Assessment (SVA) is probably the **most employed** verbal veracity assessment tool in forensic practice, accepted as evidence in Courts in North America, Austria, Germany, Sweden, Switzerland, and the Netherlands (Vrij, 2008).

Developed by Undeutsch (1967), SVA was aimed to evaluate the reliability of the testimonies of children in cases of suspect sexual abuses.

The assumption is the so-called **Undeutsch hypothesis** (Steller, 1989): the **cognitive elaboration** of a memory differs from the elaboration of an imaginative construction, and this difference should be perceivable in the features of the narratives.

SVA consists of four steps:

- 1 A preliminary analysis of the case;
- 2 A semi-structured interview aimed to get the statements of the subject;
- 3 The Criteria-Based Content Analysis (CBCA), the core of SVA;
- 4 An evaluation of CBCA through the Validity Checklist.

CBCA, in turn, consists of 19 criteria, marked as present or absent by trained evaluators.

The Validity Checklist addresses possible effects of intervening variables, such as psychological characteristics and motivation of the subject and of the interviewer.

- - Logical structure;
 - Unstructured production;
 - Quantity of details; 3
- - Contextual embedding;
 - 2 Descriptions of interactions;
 - Reproduction of conversation;
 - Unexpected complications during the (4)incident:

 - 5 Unusual details:
 - 6 Superfluous details;
 - Accurately reported details 7 misunderstood:
 - Related external associations; (8)
 - Accounts of subjective mental state; (9)
 - 10 Attribution of perpetrator's mental state;

- - 1 Spontaneous corrections;
 - 2 Admitting lack of memory;
 - Raising doubts about one's own 3 testimony;
 - 4 Self-deprecation;
 - Pardoning the perpetrator; (5)
- - 1 Details characteristic of the offense.

Laboratory studies suggest that CBCA can identify truth and lies with a degree of accuracy of around 70% (Vrij, 2008). Unfortunately, Undeutsch (1984) claimed that lab studies are not particularly useful in testing the SVA, as they lack of ecological validity.

By contrast, to evaluate field studies is often impossible as convictions and confessions, which should be used to establish the ground truth, frequently result from the employment of SVA itself.

Nevertheless, Vrij (2008) finds that one of the most reliable field studies shows *"several, albeit small, differences between truthful and fabricated statements (Lamb et al., 1997), and all of these differences were predicted by the Undeutsch hypothesis."*

Reality Monitoring (RM), developed by Johnson and Raye (1981), relies on the idea that cognitive processes related to perceived and imagined events are different.

Similarly to SVA, the RM calls for checking the presence/absence of RM criteria in the subjects' statements.

RM is not widely employed in forensic practice, maybe because it does not address directly deception.

RM criteria:

- 1 Clarity;
- 2 Perceptual information;
- 3 Spatial information;
- 4 Temporal information;
- 5 Affect;
- 6 Reconstructability of the story;
- 7 Realism;
- 8 Cognitive operations.

Bond and Lee (2005), in order to verify the presence of the RM criteria, annotated the transcripts of their interviews both manually and using the Linguistic Inquiry and Word Count (LIWC) the well known lexicon created by Pennebaker et al. (2001). In the first case the authors found differences between liars and truth tellers, in the second one they did not.

The opinion of Vrij (2008) is that "the problem with using automatic coding is that computer word counting systems ignore context, whereas the RM tool, as well as CBCA, require that the context is taken into account."

In literature, the accuracy of RM in classifying the statements is remarkable: 68.8% (Vrij, 2008).

Theoretically well-grounded on memory theory, the Cognitive Interview (CI) is a well-known protocol for testimonies' collection, widely employed in police investigations.

The tool, realised by Fisher and Geiselman (1992), is aimed to enhance the recollection of detailed information in cooperative eyewitnesses.

During the CI, are asked to carry out a number of task, such as:

- Mental reinstatement of environmental and personal contexts;
- In-depth reporting (possibly with 'think-aloud' technique);
- Reporting the event in different orders;
- Reporting the event from different perspectives.

There is experimental evidence that, compared to standard interview, CI increases the leakage of cues of deception as well (Colwell et al., 2002).

The Reid technique (Inbau et al., 2011) is a method for police interrogations, developed since 1947 and widely employed, especially in United States.

The basic idea is to put the uncooperative examinees under psychological pressure through the use of emotionally charged questions and argumentations, in order to elicit cues of deception and the confession of the crime.

The Reid techniques is criticised both for the weakness of the theoretical basis and for the risk of leading to false confessions (Gallini, 2010).

The Reid technique is a structured nine-steps process, which includes confrontation and minimalisation strategies (Moore and Fitzsimmons, 2011):

- At the beginning the suspect is informed there is evidence (either real or not) he is guilty: the subject is interrupted if he tries to deny the allegations.
- Moral justifications or rationalizations for the crime are presented, suggesting that the confession lead to leniency;
- The questions to the subject imply presumption of guilty;

"From the suspect's perspective, isolation, fatigue and fear may produce a compliant (but false) confession from a person who merely wants to extricate himself from an aversive situation and/or who succumbs to implied threats of dire consequences or implicit promises of clemency" (Moore and Fitzsimmons, 2011).

The case of Juan Rivera

"In 1993, Juan Rivera, a resident of Waukegan, Illinois, was sentenced to life in prison for the rape and murder, a year earlier, of an eleven-year-old girl".

"No physical evidence linked him to the attack".

"Nevertheless, in late October of 1992, he was brought to Lake County Jail, in Waukegan, and interrogated intermittently for four days. Twice during that time, Rivera was taken to Reid headquarters, in Chicago, where a Reid employee named Michael Masokas administered polygraph tests. The results were mixed, but Masokas told Rivera that the evidence demonstrated his guilt. Eventually, after more round-robin interrogation, he signed a confession.

Rivera's conviction was affirmed three times [...]. The last trial was, in many ways, the most astonishing, because it came four years after **new** DNA evidence had exculpated Rivera. Nevertheless, he was found guilty again, based partly on the strength of his original confession. Rivera's attorneys appealed, and he was released in 2012.".

"John E. Reid & Associates will pay two million dollars, which appears to be the largest settlement in its history" (Starr, 2015).



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Modern stylometry is the branch of Natural Language Processing (NLP) which studies texts considering their stylistic features only, making use of:

- Computational methods for automatic extraction of linguistic cues;
- Machine learning techniques for text analysis.

Stylometry has proven successful in detecting deception, dealing with:

- Spoken and written language in laboratory conditions (Newman et al., 2003; Strapparava and Mihalcea, 2009);
- Synchronous and asynchronous texts in Computer-Mediated Communication (Hancock et al., 2007; Zhou et al., 2004; Zhou, 2005);
- Spoken and written language collected on the field in judicial context (Bachenko et al., 2008; Fornaciari and Poesio, 2013).

Personality Recognition from texts is a computational linguistic task as well.

It consists in the automatic classification of authors' personality traits using textual cues as features.

Celli (2013) realised a semi-supervised system for personality recognition available online, which labels the texts with personality traits.

In the study of Fornaciari et al. (2013), deception detection and personality evaluation were combined.

The typical task of text classification was employed to explore the relationship between personality types and linguistic style in deceptive communication, making use of:

- **DECOUR**, a corpus of deceptive statements issued in high stakes conditions (Fornaciari and Poesio, 2012);
- The system of Celli (2013) for personality recognition.

In particular, models performance in detecting deception was compared with personality types of the subjects.

DECOUR - DEception in COURt - is a corpus constituted by the transcripts of 35 hearings:

- Issued by 31 subjects;
- Held in 4 Italian Courts: Bologna, Bolzano, Prato and Trento.

They come from criminal proceedings for calumny and false testimony, where:

- at least a *verbatim* transcription of a hearing exists, reporting statements of the defendant;
- the defendant is found guilty;
- a final judgment exists about the false testimony, which points out the lies told by the defendant.

The participants in the courtroom are:

- The examinee, who can have the status of witness or defendant;
- The Public Prosecutor;
- The defendant's lawyer;
- The Judge;
- · Possibly, other expert witnesses.

The analysis units are the utterances issued by the examinee..

One or more consecutive utterances constitute a turn, and each turn is delimited by the intervention of other participants.

The utterances were labeled as follows:

False. Utterances which are clearly identified as false in the judgment or which, according to identified lies, seem to be false.
True. Utterances consistent with the reconstruction of the facts.
Uncertain. Utterances related to the facts under investigation, but of which the deceptiveness is not proved. Also utterances that logically cannot be either true or false, like questions or utterances attended to the facts.

Label	Utterances	Tokens		
		with punct.	no punct.	
False	945	15924	13376	
True	1202	15456	12847	
Uncertain	868	10439	8669	
Total	3015	41819	34892	

Three coders marked about 20% of DECOUR. Kappa was used as metric for their agreement (Artstein and Poesio, 2008):

- Its value for the three classes was k = .57;
- The value for two classes false vs. true and uncertain utterances was k = .64: a moderate (Carletta, 1996) or substantial (Landis and Koch, 1977) agreement.

Personality is defined as an affect processing system that describes **persistent** human behavioural responses to broad classes of environmental stimuli (Adelstein et al., 2011) and characterizes a unique individual (Mairesse et al., 2007).

Differences in personality appear to include the style used in deception: e.g., several personality factors appear to correlate with the ability of a judge to detect deception (Enos et al., 2006).

Personality can be assessed by means of different questionnaires, such as the **Big5** (Costa and MacCrae, 1992), that defines five bipolar traits and has become a standard over the years.

The dimensions of the Big5 were employed for the analyses of Celli (2013).

The Big Five personlity traits

Extraversion. It describes a person along the two opposite poles of sociability and shyness.



Emotional stability. Sometimes referred by its negative pole (neuroticism), Emotional stability describes the modality of impulse control along a scale that goes from control (a calm and stable person) to instability (an anxious and neurotic person).

Agreeableness. Agreeableness refers to the tendency to be sympathetic and cooperative towards others, rather than suspicious and antagonistic.

Conscientiousness. Conscientiousness describes a person in terms of self-discipline versus disorganization.

Openness. Openness to experience refers to the tendency to be creative and curious rather than unimaginative.

Features for personality recognition

As initial feature set, the system exploits language-independent correlations as features. These are taken from LIWC and MRC, whose correlations to personality are reported by Mairesse et al. (2007).

Feature	Ext.	Emo.	Agr.	Con.	Ope.
Punctuation	08**	04	01	04	1**
! marks	0	05*	.06**	.00	03
Word freq	.05*	06**	.03	.06**	07**
Numbers	03	.05*	03	02	06**
Parentheses	06**	.03	04*	01	1**
? marks	06**	05*	04	06**	.08**
Quotes	.05*	02	01	03	.09**
Repetitions	.05**	.1**	04*	05*	.09**

Correlations are used as a model in a semisupervised way:

- in the preprocessing phase, labels are generated to retrieve label distribution;
- in the processing phase, labels are recomputed and filtered on the basis of the distribution found in the previous phase.

This system for personality recognition is the first to have been tested both on English and on Italian, obtaining F-measures between .63 and .68.


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• In the end, we carried out a Multi-Dimensional Scaling - MDS Baayen (2008), in order to visualize the distances between our subjects, according to their personality traits. In particular, we used the MDS charts to compare the performance of the models with the different personality types of the subjects.

We trained models in order to **classify** the utterances of DECOUR, according to the classes they belong to.

We tested a variety of classification methods, finding that the best performance was obtained with Support Vector Machines (SVMs) (Cortes and Vapnik, 1995).

Our SVM models were trained and then tested via *n*-fold cross-validations. In each experimental condition, the hearings of DECOUR constitutes the folds for the cross-validations, so that the experiments were carried out with a 35-fold cross-validation.

The single utterances were our analysis units and they were described by vectors whose the values were the frequencies of *n*-grams of lemmas and part-of-speech (POS), collected separately form false and true utterances (the uncertain ones were not employed in the feature selection).

In order to select the features, we computed the Information Gain - IG (Forman, 2003) of the *n*-grams of lemmas and POS whose the frequency in DECOUR was > 5, and we selected the *n*-grams having an IG value > .01.

The performance of the models was evaluated according to:

- majority baseline;
- a simple heuristic baseline:
 - The utterances beginning with the words Si (Yes), Lo so (I know) and Mi ricordo (I remember) are classified as true;
 - The utterances beginning with the words No (No), Non lo so (I don't know) and Non mi ricordo (I don't remember) are classified as false;
 - All other utterances are randomly classified as true or false, according to the rate of true and false utterances present in DECOUR.

In the first experiment, we used personality traits as features for the classification task of the utterances in DECOUR as true or false.

Algorithm	Acc.	M. Precision	M. Recall	F-measure
mbl (zeroR)	.5598	.313	.56	.402
dt (J4.8)	.5803	.579	.586	.55
nb (NaïveBayes)	.5631	.548	.562	.538
svm (SMO)	.5850	.582	.585	.533
ripper (JRip)	.5808	.576	.582	.532

Majority baseline: 55.98% Heuristic baseline: 59.57%

Surface features for deception detection

False vs. Not-False utterances classification			
	Correctly	Incorrectly	
	classified entities	classified entities	
False	342	284	
Not-False	1786	603	
Total accuracy	70.58%	29.42%	
Majority baseline	68.66%		
Heuristic baseline	62.39%		

False vs. True utterances classification

	Correctly	Incorrectly
	classified entities	classified entities
False	511	234
True	968	434
Total accuracy	68.89%	31.11%
Majority baseline	55.98%	
Heuristic baseline	59.57%	

MDS - Personality and performance



In red the performance below the heuristic baseline.

Results

In DECOUR we have only 35 hearings and we found only 9 personality types, out of 120 possible profiles (five-factorial): the evaluation of the results must be prudent.

Personality traits are not particularly useful to detect deception at utterance level, since they supposedly identify the liars rather than the lies.

However:

- In the False vs. Not-False utterances experiment MDS seem to not show a clear pattern.
- In the False vs. True utterances experiment two clusters appeared. The T-Test confirmed that their accuracies belong to different populations.

The models performed better for subjects:

- extrovert, even though many subjects seemed to be introvert;
- friendly;
- organized;
- insightful, even though this trait belong to subjects difficult to be classified.

Instead, the models' performance was lower for subjects:

- uncooperative;
- secure. By contrast, most people seemed to be neurotic: this is probably due to the stress of the situation.

Outline





4 Verbal behavior

5 NLP



Conclusion Cross-disciplinarity The role of DD Future perspectives Computational linguistics The results of the studies on deception detection from different research field allow to draw some general conclusions:

- The perfect cue of deception, the Pinocchio's growing nose does not exist;
- A number of variables (most of them difficult to control in lab conditions) can affect the expression of possible cues of deception, so that in many cases the findings are inconsistent.
- Even in the few cases where the correlation between cue and deception is consistently found, the effect of the cues is weak;
- Deception detection can be improved by the evaluation of cluster of cues, even though their composition and their evaluation must take into account the operational context.

Every technique for detecting deception produces predictions whose the value is **probabilistic**.

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Therefore, the outcomes of Deception Detection analyses in criminal proceedings:

- Are not suitable for leading the final decision of the judge;
- · Can represent a useful support for investigations:

Given the scarce reliability of the cues of deception, Vrij and Granhag (2012) suggest to focus not on finding out new cues - which is probably an approach doomed to fail - but on manipulating the interactions with the subjects, in order to enhance the expression of the deception clues already known.

Basically, two ways can be chosen:

Imposing emotional load. This is the path followed, for example, in the Reid technique (Inbau et al., 2011). The problem is that cues of emotions are not specific of deception.

Imposing cognitive load. By contrast, the idea of Vrij and Granhag (2012) is that increasing the cognitive load of the tasks does not affect remarkably the behavior of the truth-tellers, while enhances the leakage of cues of deception from liars: *"if lying requires more cognitive resources than truth telling, liars will have fewer cognitive resources left over."*

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- The methods do not even require the interaction with the subjects;
- Linguistic analyses can be employed jointly with any paradigm of information assumption and with any other technology;
- The performance in detecting deception is similar to that of other methods.

Computational linguistics

Thanks!



Gustav Klimt, *Nuda Veritas*, 1899 Österreichisches Theatermuseum - Vienna

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