





Theme Data, Social Media, and Trust

InfoSys 2025 & InfoWare 2025

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LISBON

March 2025







Moderator

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Panelists

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Chair Introduction

- We live in a time of change
 - Deep fakes
 - Reputable institutions are behaving increasingly erratically
- As a consequence we are losing one of the last certainties about what is true and what is false
- Over 5 billion social media users (statistica, feb. 2025)
- Fake news can be dangerous for both democracy and the individual



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Andreas Schmidt

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Chair Introduction

- There is now a dedicated industry for generating fake news
- Fake news plays different roles on different social networks (Stack Overflow, Coursera vs. twitter, facebook)
- Question: What can be done, that the information in social networks would become more trustworthy?



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What can be done against fake news?

- Legal ban on fake news
- Platform operators monitor the messages and eliminate/sanction fake news (use of AI)
- Involving (independent) fact checkers
- Users are critical of sensational news and check it for accuracy before sharing it
- Integration of a trust and reputation component
- A combination of above ...



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- There has always been fake news, propaganda, misinformation
 - There have always been attempts to restrict or license publications
 - Licensing for printers, for plays, book censorship, nihil obstat etc
 - Pressure always for democratization of means of communication
- The Internet certainly makes things worse
 - Governments try to restrict access to that too
 - Samizdats have always been more popular than official news
- Technical ways for checking authentication with live source
 - But no way to verify author of a forwarded message (even PGP)
 - Published information is always suspect, avoid single source of news



Malcolm Crowe, UWS UK

Data vs Social Media:

- Social media is for opinion, reaction, likes, advice
- Don't look for data in social networks
- Some AI tools try to incorporate both is this helpful?
- A bigger problem: fake news about new technology, science etc
 - Claims that COVID, climate change etc are hoaxes, 5G a killer
 - Claims that vitamins can cure cancer, vaccines are deadly
 - Over-hyped software (especially AI tools)
- Another problem: software generated by AI
 - Built-in bias or second-hand information, AI hallucinations
 - The software industry needs to step up, clean up its act

Malcolm Crowe, UWS UK



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Fritz Laux Reutlingen University

Misinformation and Fake News

My Position

IARIA

- Misinformation and Fake News are not limited to Social Media
 - They have been around since the beginning of mankind
 - But now, it have the possibility to multiply indefinitely.
- Sources of different levels and varying degrees of trustworthiness
 - Generally, the greater the effort, the more reliable the information
 - But, there are exceptions → difficult to identify trustworthy information
- Both statements are obvious
 - But, how can we identity Misinformation and Fake News?





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Fritz Laux Reutlingen University

Lisbon Misinformation and Fake News **March 2025**

My Position

- Strategies to identify Misinformation and Fake News
 - Always question information \rightarrow look for other sources
 - Use known trustworthy sources to crosscheck
 - Think critically about and make plausibility checks
- Example (1/3)
 - Professors retiring in Germany from 2023 2033:
 - ~ 45% = 2000 /year (source: Spiegel, CHE, destatis)
 - \checkmark This is a plausible information, because
 - \checkmark Reliable sources
 - \checkmark Easy to verify with basic arithmetic, if you know the total number (~50 000) and avg. age 41 when becoming tenured professor (~22 years on duty)



52%

wer beschäftigte hauptberufliche Professorinnen und Professoren

95

Nachgezählt

Rechts-,

Wirtschafts-

wissenschaften

39%.

5177 Personen

G. Ouellen: CHE. Destatis

und Sozial-



IARIA

Fritz Laux Reutlingen University

Misinformation and Fake News

My Position

Example: (2/3)

- China is accused of harvesting organs from Falun Gong prisoners (China Tribunal and many others)
 - ✓ Number of organ transplants performed in China grew rapidly which corresponds with the onset of the persecution of Falun Gong
 - ✓ Verified by <u>Kilgour-Matas-Gutmann</u> investigation report: indirectly verified by the amount of immune suppressants used by China & known sources of organs.
 - ✓ The Wikipedia article is a good example how investigators gather and use evidences
 - ✓ 172 sources of information cited in the English version, the German version is more critical and misses neutrality
- Example (3/3)
 - Ukraine Military Situation: number of killed soldiers on both sides
 - ✓ Dozens of reports weekly
 - ✓ Most information comes from parties involved in the war and have a clear interest in misinformation.
 - \checkmark "The first victim of war is the truth" (Senator Hiram Johnson) . Targeted disinformation!
 - ✓ The losses in the Ukrainian War are NOT verifiable (at the moment)



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• Algorithmic Bias - Understanding and Mitigation

Algorithmic bias occurs when AI systems make decisions that are systematically unfair to certain groups.

Examples: biased facial recognition, hiring algorithms, and loan approval systems

Causes:

- Data Bias: Biased training data reflecting historical prejudices
- Model Bias: Biases introduced during model development and training
- Interpretation Bias: Misinterpretation of AI outputs by users
- Mitigation Strategies:
 - Diverse Data Sets: Use diverse and representative data sets
 - Bias Audits: Regularly audit AI systems for bias
 - **Transparency:** Ensure transparency in AI decision-making processes



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Machine Unlearning - Enhancing AI Fairness and Compliance

- Involves selectively removing data points from AI models to ensure data privacy and compliance.
- Helps AI systems "forget" specific information, improving fairness and accuracy
- Importance:
 - Data Privacy: Ensures compliance with data protection regulations like GDPR
 - Fairness: Helps eliminate biases by removing problematic data
 - Model Performance: Maintains/improves AI system performance by addressing data removal requests
- Challenges:
 - Technical Complexity: Retraining models without specific data points can be resource-intensive
 - Ethical Considerations: Balancing data removal with the need for accurate and fair AI models



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The need for trustworthy data sources for building ML models

Problem is not AI-technology but qualitative, diverse data sources
No shortage of AI specialists, no shortage in processing power → Shortage is in qualitative data

Data spaces as an enabler for large-scale distributed data sources

- Domain-specific data marketplaces enable long-standing collaborations between data owners and processors
- Quality seals to increase trust during negotiations → Scope, anonymity, utility

Anonymized data to the rescue!

- Enable data disclosure and data collaborations, while also preventing sensitive data leakage from ML models
- Federated learning is often not the silver bullet → a lot of trust required in central party and/or peers

Are synthetic data the holy grail?

- Alternative for statistical data-anonymization with lot of interest from industry
- Currently not the one-size-fits-all solution, both in terms of data utility and data privacy



Michiel Willocx DistriNet – KU Leuven Belgium



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Non-portable AI/ML models – Understanding and Mitigation

- (Def.) A homogeneous data source (HDS) is a data source that generates similar data points. *Ex.:* A certain geographic area.
- (Def.) Non-portable model: A "non-portable" model refers to a model that cannot be (easily) transferred from one HDS to another for the same problem.

Example:

- Consider the **problem of modeling wildfire** for predicting **spread of fire**, **next-day fire**, **total burned areas**, ...
- HDS 1: California (2025 fire)
- HDS 2: Alberta, Canada (2016 Fort McMurray fire)



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Causes:

- HDS have unique characteristics

Examples of unique characteristics (Wildfire modeling)

- Fuel type
- Weather
- Elevation

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Problem: Model(HDS 1) cannot be effectively used in HDS 2.

Mitigation: ??



Resume Panel #1



- We need a detailed definition of "fake news" In this context, perspective and perception play a particularly important role.
- Social networks are often about opinions and less about facts
- Reliable sources are essential tools for verifying facts in social media.
- Fact checking is a complex and time-consuming process
- LLMs can probably be used to identify "fake news" (or at least support the process of fact-checking)
- "Data Spaces": Resource for trustworthy AI models for the future
- Bias in data Bias is reality How can we handle it?