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Plaintext: A Missing Feature for Enhancing the Power of Deep Learning in Side-Channel Analysis?

Breaking multiple layers of side-channel countermeasures

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Outline

- Background and ASCAD database
- Attack model
- Plaintext feature in SCA
- Proposed CNNP models: hyperparameter and models
- Experimental conditions and reference models
- CNNP models evaluation
- Discussion

Side-channel Analysis (SCA)

- When an electronic device operates, it can leak data through side-channels, such as via power consumption, EM fields, timing
- Even though the cryptographic algorithm is secure in theory, secret information can be revealed from side-channel information
- SCA-based attacks like DPA and CPA are well known since 1996
- More recently, shown that machine learning can learn from side-channel information to reveal the secret key of a cryptographic device

Convolutional Neural Network (CNN)

- Can learn from unaligned data
- Includes a number of layers:
  - **Convolutional layers** based on a number of filters to detect features of the data
  - **Pooling layer** is used to reduce size of the parameters to be learned
  - **Fully connected layer** combines all previous features (nodes) together
  - **Dropout layer** is used to prevent over fitting by randomly removing a number of detected features (nodes)
- Activation functions
  - **Rectified Linear units** introduce non-linear computation into the output of a neuron
  - **Softmax** is used to handle the final classification

Evaluated AES implementation with SCA countermeasure (from ASCAD Database)

https://www.data.gouv.fr/en/datasets/ascad/

- Software implementation on 8-bit AVR ATMega 8515 microprocessor
- Two masks are used for
  - Plaintext

$$\overline{p_i} = p_i \oplus m_i$$

  - SBox

$$\overline{SBox(x)} = SBox\left(x \oplus m_{i,in}\right) \oplus m_{i,out}$$

ASCAD database

- Targeted the third sub-key, which is protected by two kinds of masking
- Fixed key dataset
  - Same key used for learning and testing
  - Trace length: 700 points
  - Training group: 50,000 traces
  - Testing group: 10,000 traces
- Variable key dataset
  - Random keys used in training data group and fixed key used in testing data group
  - Trace length: 1,400 points
  - Training group: 200,000 traces
  - Testing group: 100,000 traces
- Synchronized, desynchronized datasets are available

Attack model

- Attack on the output of the 3rd SBox in the 1st round of AES
- Classification uses the output value of SBox (256 classes)

$$SBox(p_2 \oplus k_2)$$

Plaintext feature in SCA

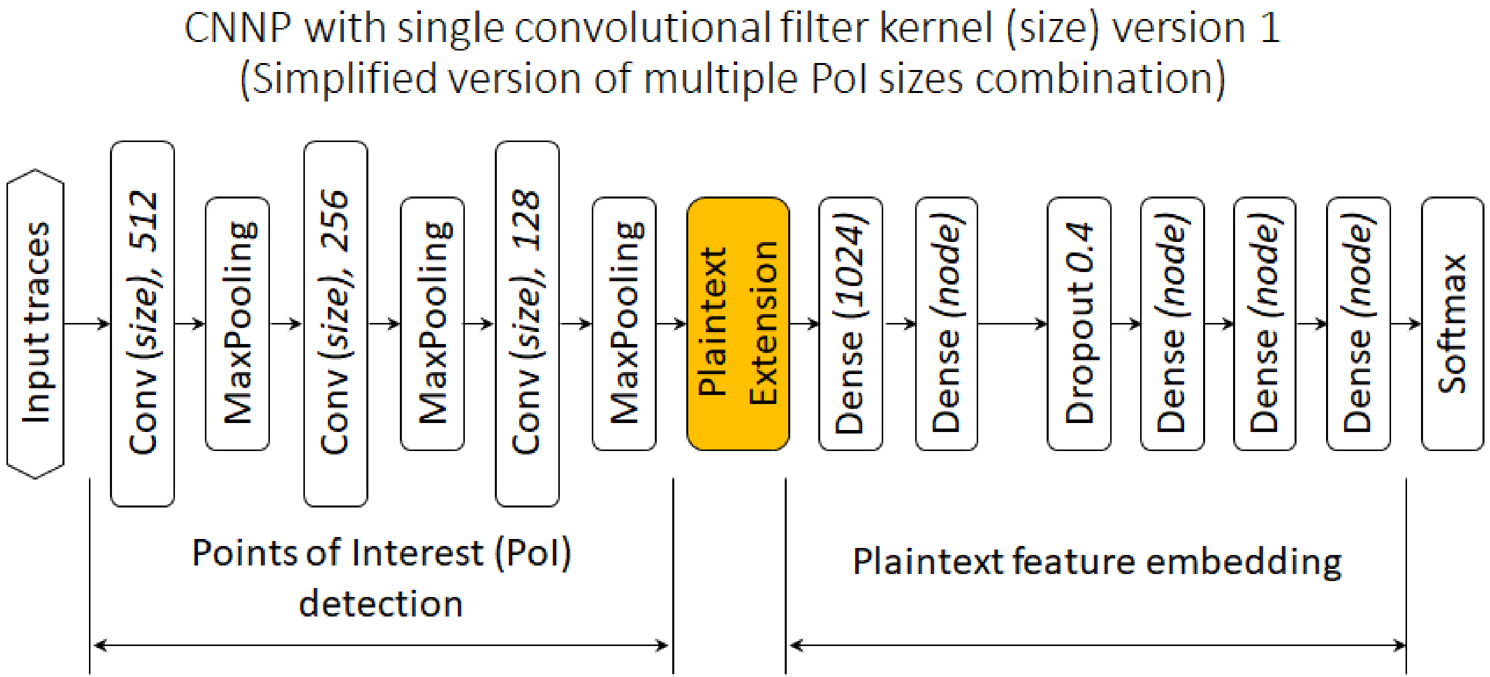
- Inputs that effect a power trace:
  - Plaintext (or ciphertext)
  - Masks
  - Key
- Providing plaintext or ciphertext reduces the number of unknown factors
- Plaintext feature is added using two methods: integer and one-hot encoding, where the feature is shown by a single number or a sparse vector

Proposed CNN model and hyperparameter selection

- Convolutional filter kernel sizes range from 3 to 19
- MaxPooling is used for local point of interest selection
- Convolutional layers have 64, 128, 256 and 512 filters
- Five fully connected layers of 1024 and 512 neurons each
- Activation function: ReLu

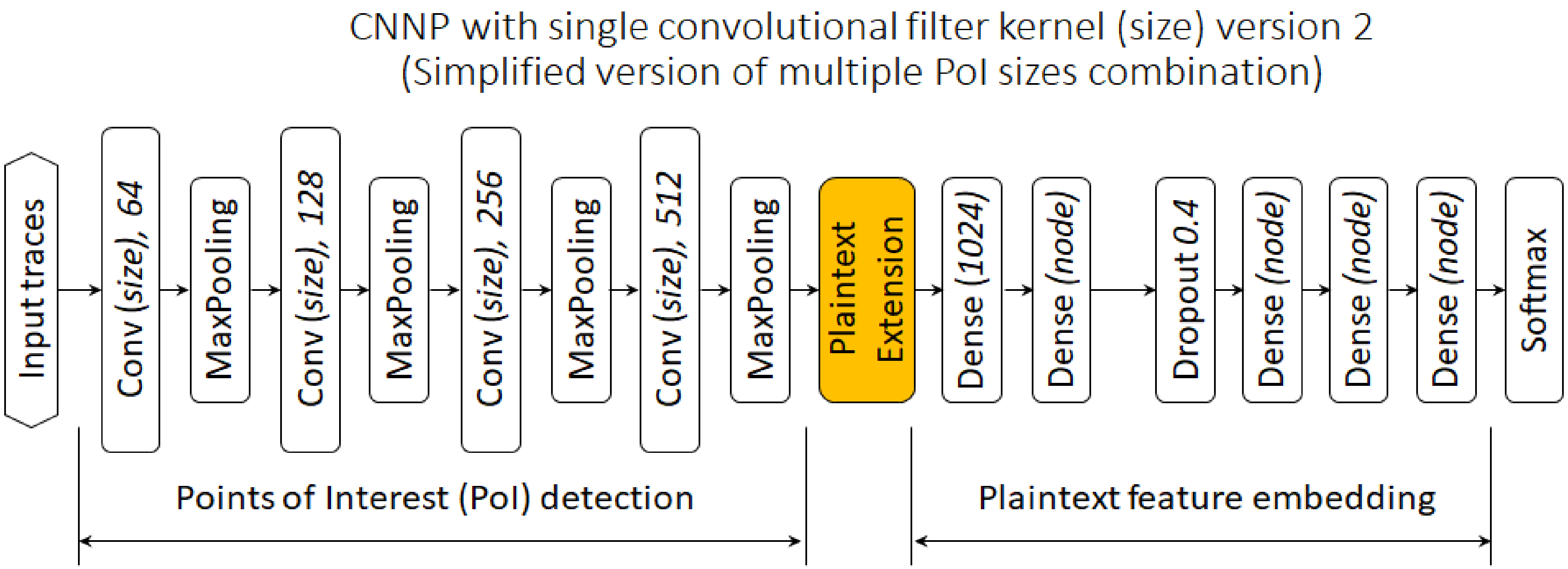
CNN with Plaintext extension (CNNP) – Model 1

- Three convolutional layers
- The number of convolutional filters reduces from 512 to 128
- Maxpooling is used for feature finding
- Finding features are extended with Plaintext



- Five fully-connected layers are used to compile the features extracted from the previous layers
- Over-fitting is prevented by using dropout

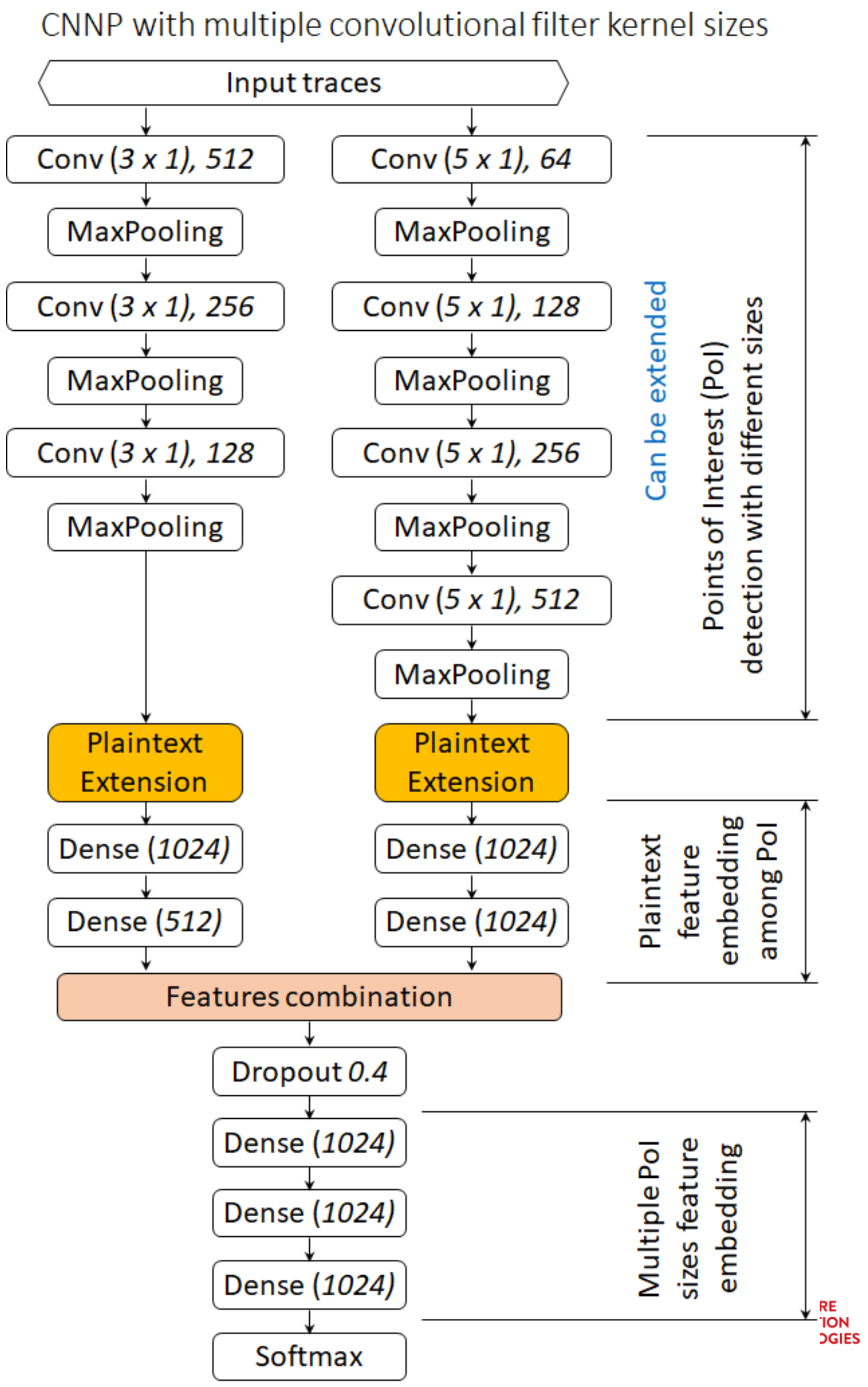
CNN with Plaintext extension (CNNP) – Model 2



- Four convolutional layers used
- The number of convolutional filters increases from 64 to 512
- Plaintext feature is extended by connecting to the detected features
- Five fully-connected layers are used

CNNP model extension

- Combination of CNNP models 1 and 2 using transfer learning
- Two fully-connected layers are used to compile the features extracted from each CNNP model before combination
- Three other fully-connected layers are used to combine the combination features
- Feature combination layer must be located after the fully-connected layers of the two CNNP sub-models



Attackers knowledge & experimental conditions

- Assumption about attacker:
  - Knows plaintext / ciphertext
  - Aware of SCA countermeasure but not aware of the detailed design and random mask value
  - Can profile keys on the implementation
- Hypothesis keys are ranked using Maximum likelihood score
- Training is performed on VMware hosted Ubuntu with access to virtual NVIDIA GRID M60-8Q and M40-4Q GPUs.

SCA reference models

We compare our profiling results with 4 publicly available models (ASCAD database)

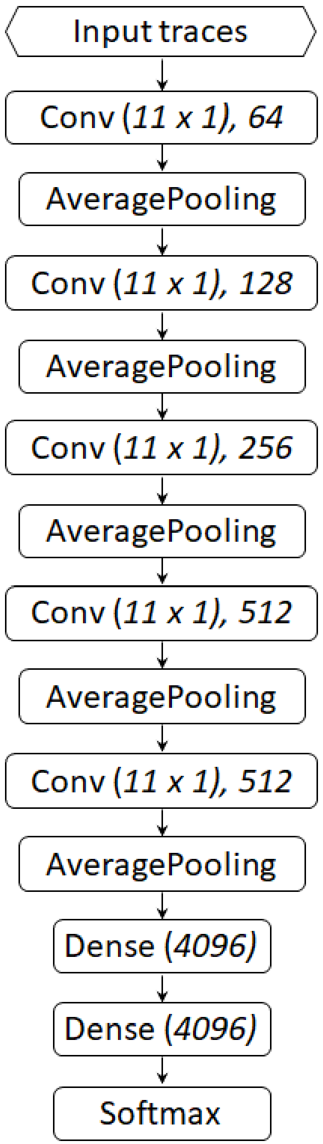
- Template attack
- Multilayer perceptron model with 5 hidden layers, 50 neurons each
- Multilayer perceptron model with 5 hidden layer - 700 neurons in first layer & 200 neurons in subsequent layers
- VGG-16 based CNN model

VGG16 Vs CNNP Models

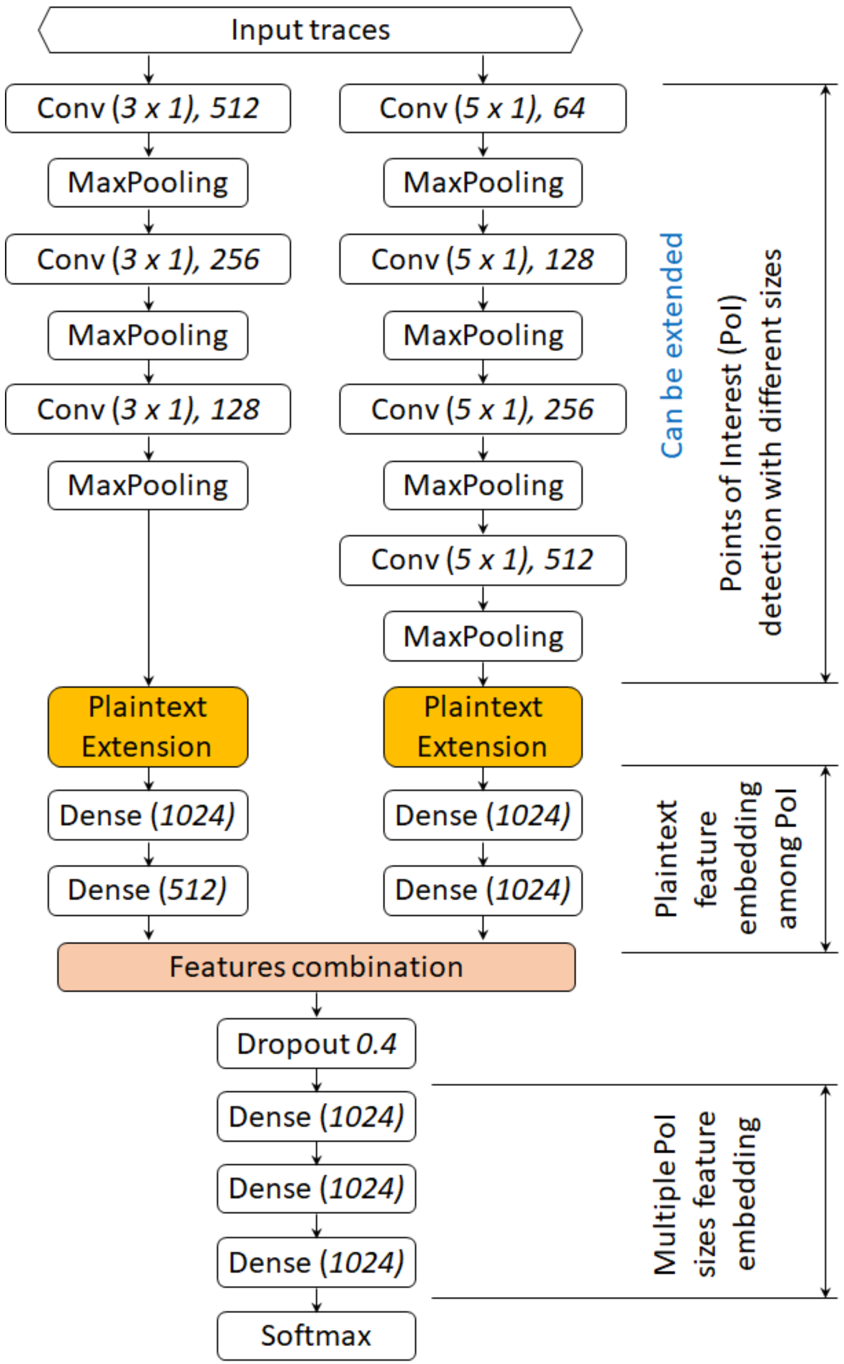
In comparison to the VGG-16 based model, the CNNP model:

- is deeper but narrower
- has less convolutional layers
- utilizes smaller convolutional filter kernel size
- uses MaxPooling instead of AveragePooling
- includes plaintext as an additional feature

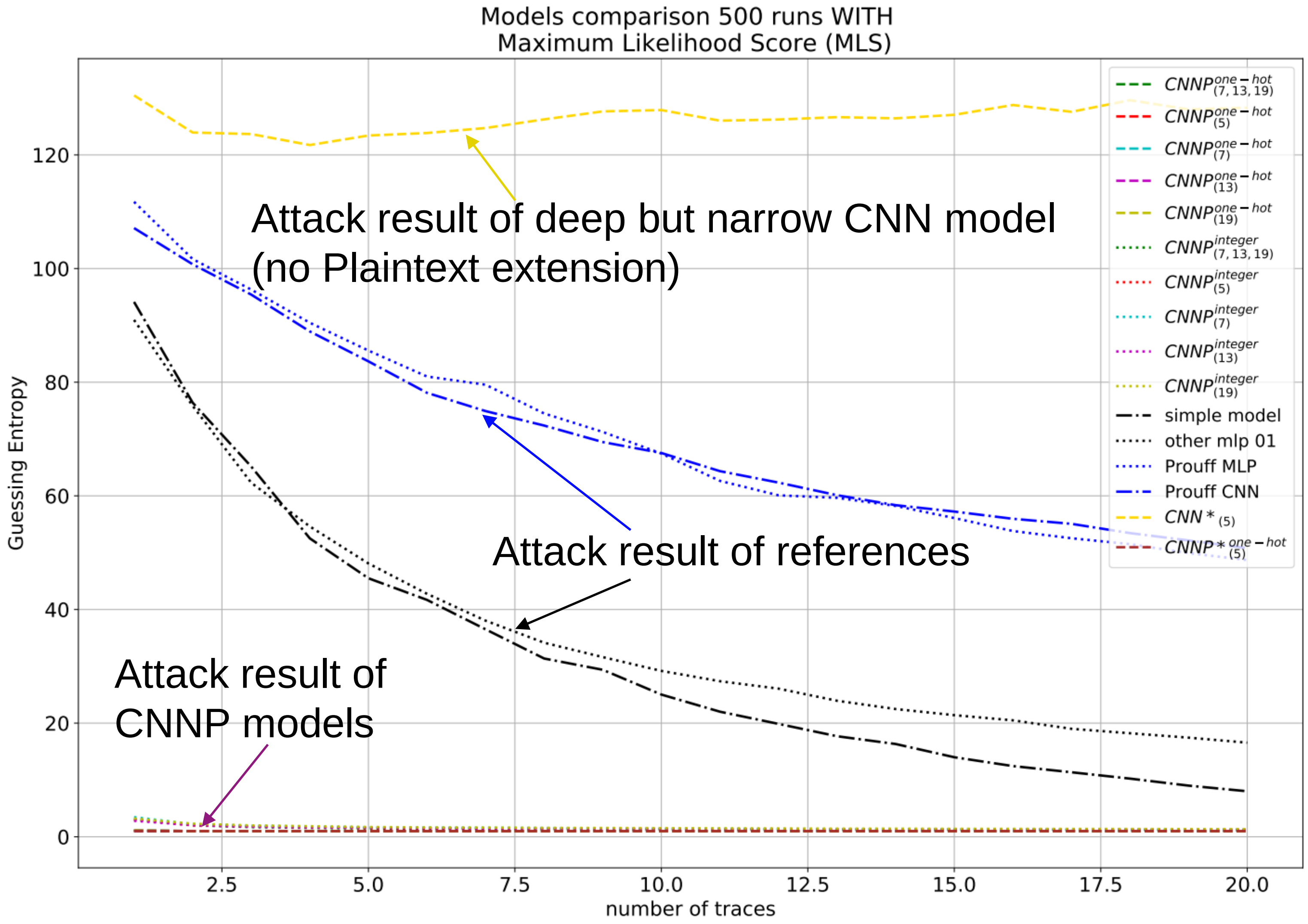
VGG-16 based CNN model



CNNP with multiple convolutional filter kernel sizes

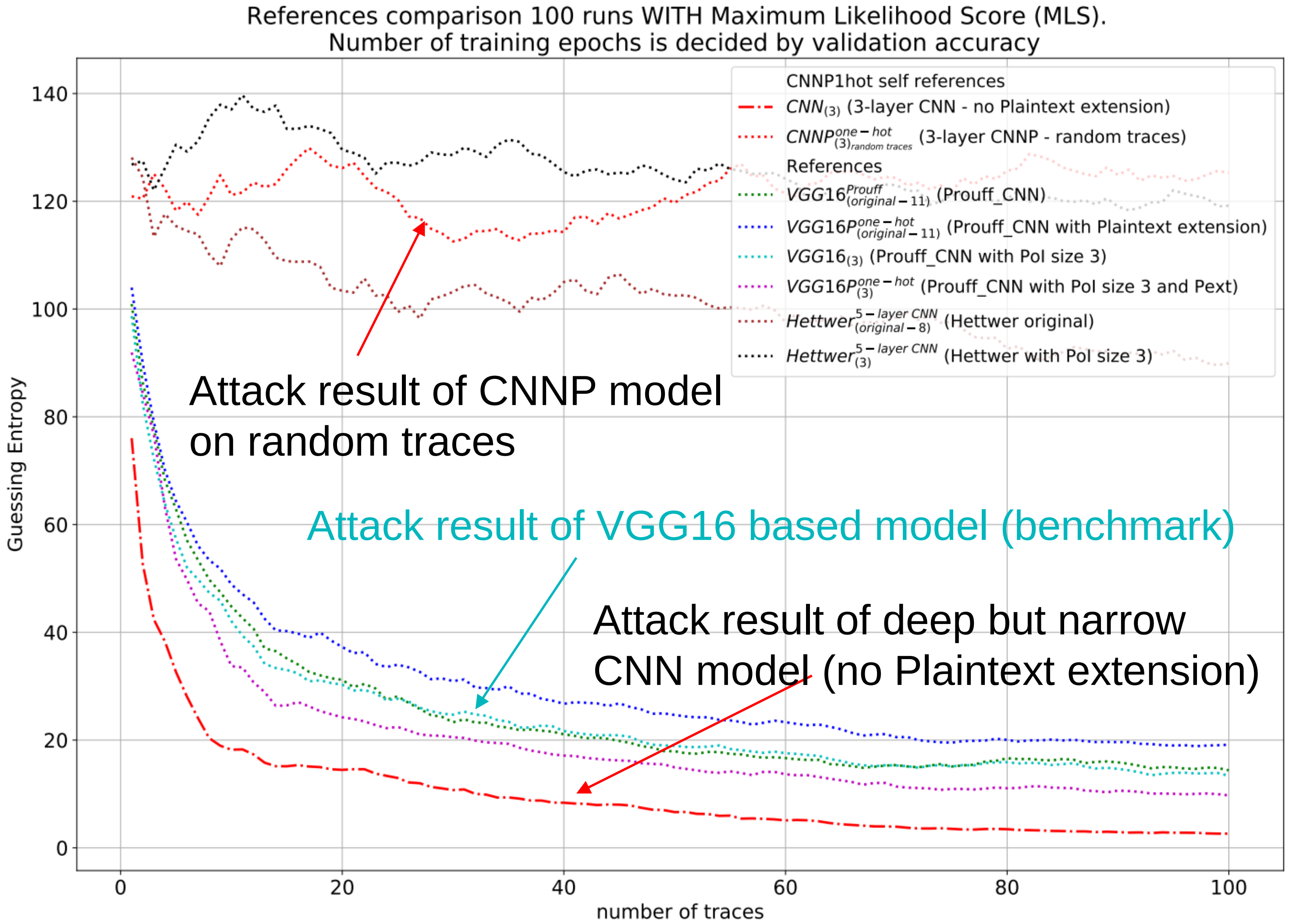


Evaluation of CNNP models on ASCAD fixed key dataset



- CNNP model can reveal the secret key within 2 traces
- CNNP models relies on the bijection $S[(.) \oplus K]$ to reveal K without using traces
- Plaintext feature encoded by one-hot encoding achieves better result than with integer encoding

Evaluation of CNN models on ASCAD variable key synchronized dataset



- An additional reference model which refers to plaintext as a feature is included
- Proposed deep but narrow CNN model is better than all other models in revealing the secret key
- CNNP model on variable key relies on both plaintext and traces to learn

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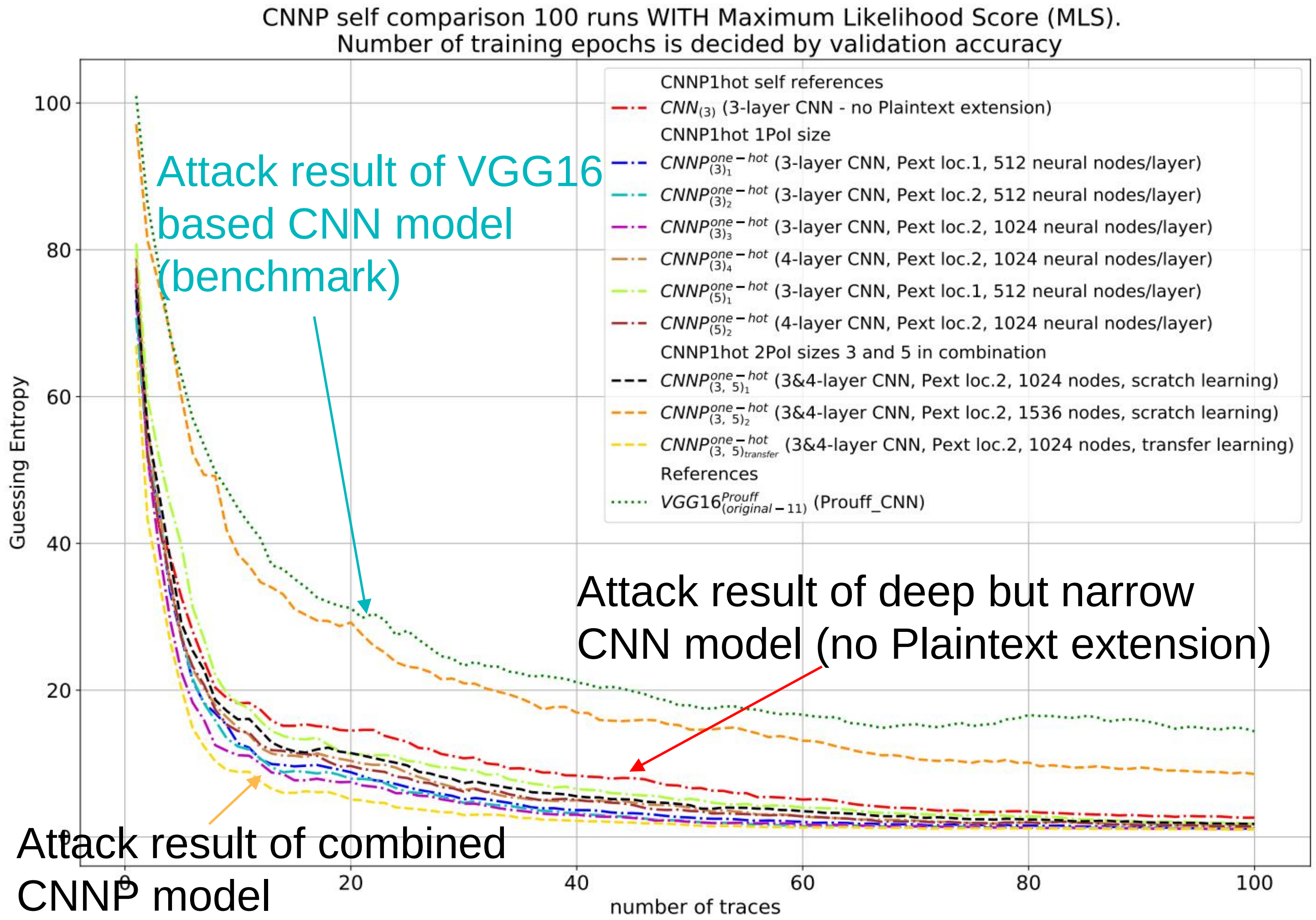
Comparison of CNNP models on ASCAD synchronized dataset with variable key



- Both CNNP model 1 and 2 are better than VGG16 and and can achieve rank 3 and 5 for the 3rd subkey with 40 traces
- Smaller convolutional filter kernel size (e.g size 3) is more efficient than larger one (e.g. size 5)
- Combination of the 2 models with transfer learning achieves the best result

Discussion

- Effect of convolutional layers and filter sizes
  - Help to find the feature regardless of misalignment in the traces.
  - Small convolutional kernel size works better than larger kernel sizes
- Effect of Plaintext feature extension and location
  - Plaintext feature extension reduces the number of unknown factors that contribute to features in the traces
  - Location of plaintext feature has less effect on the result
- Effect of network structure
  - Deep but narrow network shows better attacking result than wide but shallow ones

Thank you

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