Doubly Convolutional Neural Networks

SMAI Project

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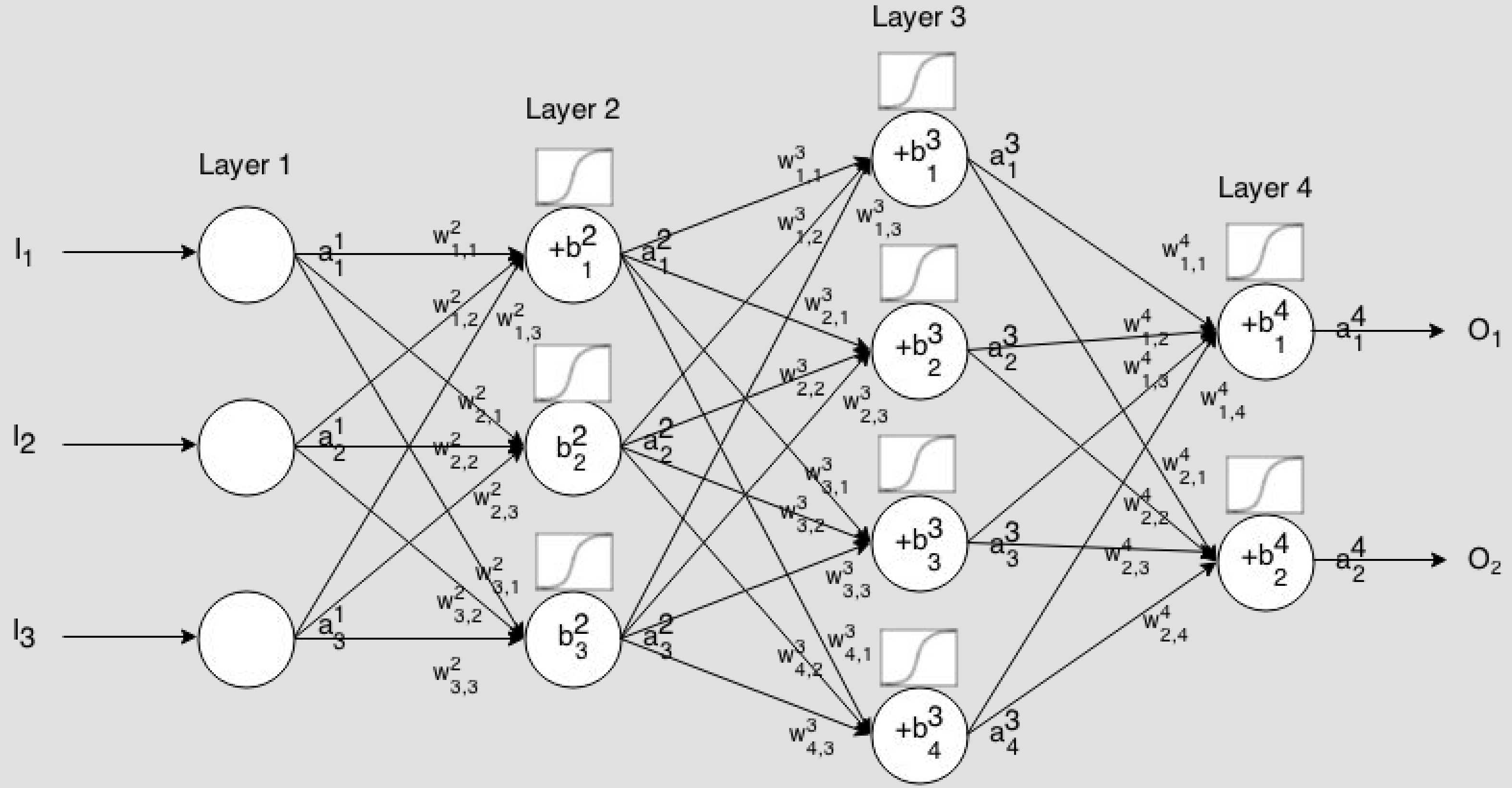
AIM

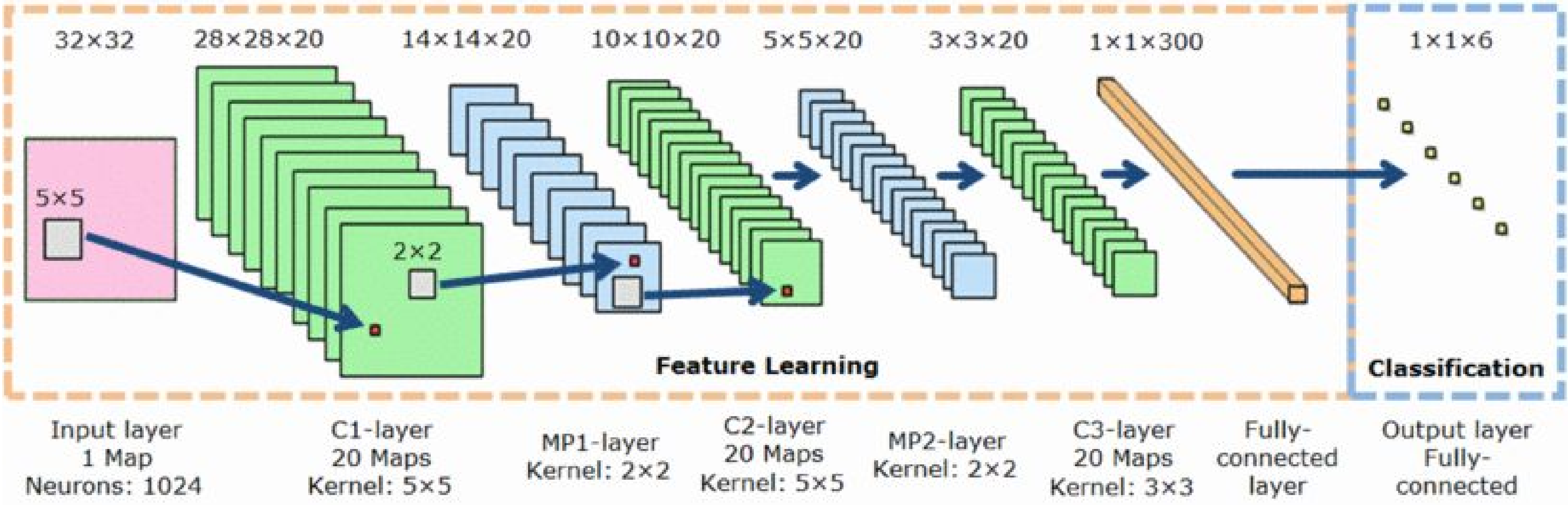
Parameter sharing is the major reason of success of building large models for deep neural networks. This paper introduces the idea of **Doubly Convolutional Neural Networks**, which significantly improves the performance of CNN with the same number of parameters.

Neural Network



Convolutional Neural network

CNNs are extremely parameter efficient due to exploring the translation invariant property of images, which is the key to training very deep models without severe overfitting.



K-Translation Correlation

In well trained CNNs, many of the learned filters are slightly translated versions of each other.

K-translation correlation between two convolutional filters within same layer W_i, W_j is defined as:

$$\rho_k(\mathbf{W}_i, \mathbf{W}_j) = \max_{x,y \in \{-k,\ldots,k\},(x,y)\neq(0,0)} \frac{< \mathbf{W}_i, T(\mathbf{W}_j, x, y) >_f}{\|\mathbf{W}_i\|_2 \|\mathbf{W}_j\|_2}$$

Here, T(.,x,y) denotes the translation of the first operand by (x,y) along its spatial dimensions.

K-translation correlation between a pair of filters indicates the maximum correlation achieved by translating filters up to k steps along any spatial dimension.

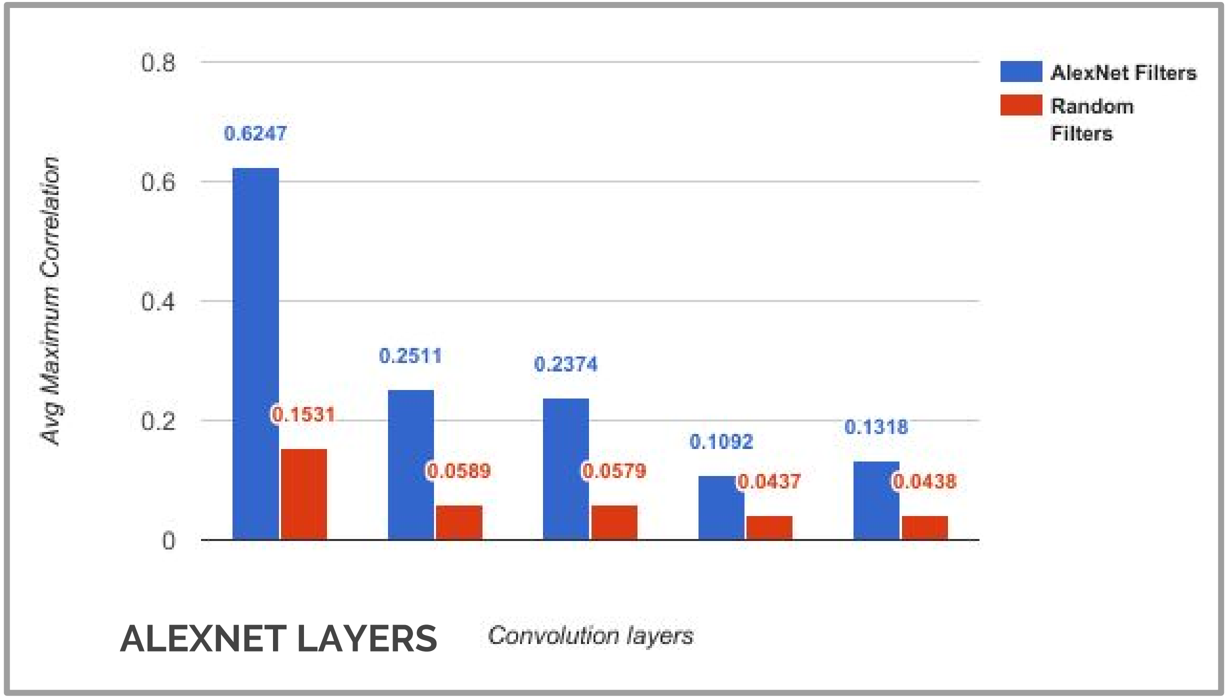
For deeper models, averaged maximum k-translation correlation of a layer **W** is:

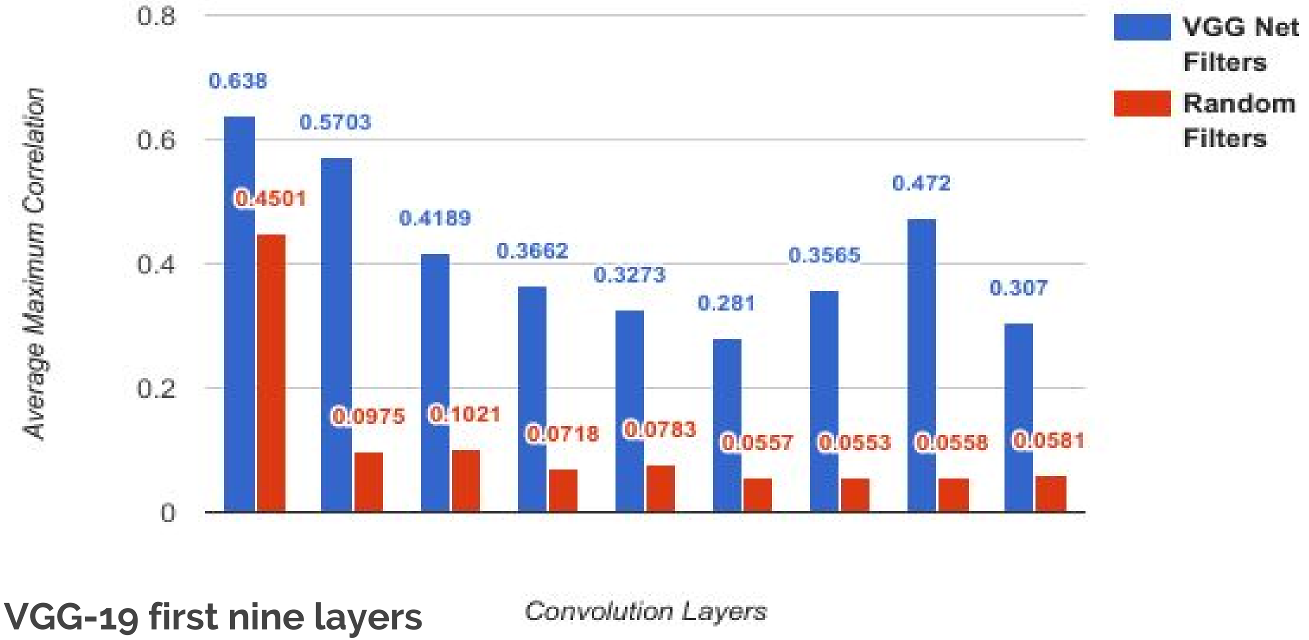
$$\bar{\rho}_k(\mathbf{W}) = \frac{1}{N}\sum_{i=1}^{N} \max_{j=1, j\neq i}^{N} \rho_k(\mathbf{W}_i, \mathbf{W}_j)$$

N is the number of filters

Correlation Results

The averaged maximum 1-translational correlation of each layer for AlexNet and VGG Net are as follows. As a comparison, a filter bank with same shape filled with random gaussian samples has been generated.





VGG-19 first nine layers

Idea of DCNN

Group filters which are translated versions of each other.

DCNN allocates a set of meta filters

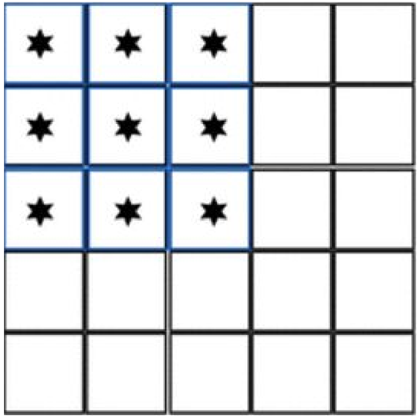
Convolve meta filters with identity kernel

Effective filters extracted

Convolution

$$\mathcal{I}^{\ell+1}_{k,i,j} = \sum_{c' \in [1,c], i' \in [1,z], j' \in [1,z]} \mathbf{W}^{\ell}_{k,c',i',j'} \mathcal{I}^{\ell}_{c', i+i'-1, j+j'-1}$$

$$k \in [1, c^{\ell+1}], i \in [1, w^{\ell+1}], j \in [1, h^{\ell+1}].$$



Input image: $\mathcal{I}^{\ell} \in R^{c^{\ell} \times w^{\ell} \times h^{\ell}}$

Set of c_{l+1} filters : $\mathbf{W}^{\ell} \in R^{c^{\ell+1} \times c^{\ell} \times z \times z}$ ***each filter of shape: c^l x z x z***

Output image: $\mathcal{I}^{\ell+1} \in R^{c^{\ell+1} \times w^{\ell+1} \times h^{\ell+1}}$

Double Convolution

$$\mathcal{O}_{i,j,k}^{\ell+1} = \mathbf{W}_k^{\ell} * \mathcal{I}_{:,i:(i+z-1),j:(j+z-1)}^{\ell},$$

$$\mathcal{I}_{(nk+1):n(k+1),i,j}^{\ell+1} = pool_s(\mathcal{O}_{i,j,k}^{\ell+1}), n = (\frac{z' - z + 1}{s})^2$$

$$k \in [1, c^{\ell+1}], i \in [1, w^{\ell+1}], j \in [1, h^{\ell+1}].$$

Input image: $\mathcal{I}^{\ell} \in R^{c^{\ell} \times w^{\ell} \times h^{\ell}}$

Output image: $\mathcal{I}^{\ell+1} \in R^{nc^{\ell+1} \times w^{\ell+1} \times h^{\ell+1}}$

Set of c^{l+1} meta filters: $\mathbf{W}^{\ell} \in R^{c^{\ell+1} \times c^{\ell} \times z' \times z'}$ *with filter size z'xz', z'>z*

Spatial pooling function with pooling size *s x s*

Working of DCNN

Set of c^{l+1} meta filters size (z' x z')

Image patches size (z x z) convolved with each meta filter

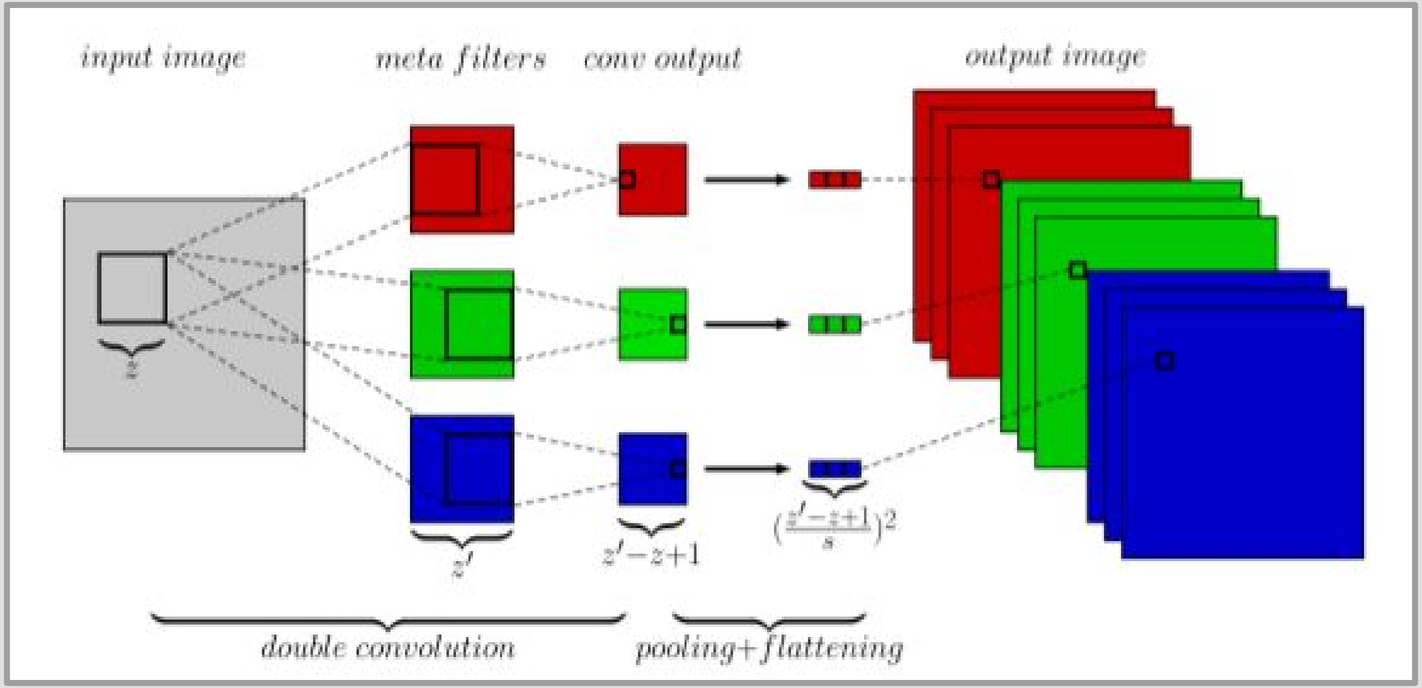
Output size (z'-z+1) x (z'-z+1)

Spatial pooling with size (s x s)

Output flattened to column vector

Feature map with nc^{l+1} channels

Double Convolution: 2 step convolution



<u>STEP1:</u> An image patch is convolved with a metafilter.

<u>STEP2:</u> Meta filters slide across to get different patches, i.e. convolved with the image.

ALGORITHM

Algorithm 1 Implementation of double convolution with convolution.

Input : Input image $I^l \epsilon R^{c^l * w^l * h^l}$, meta filters $W^l \epsilon R^{c^{l+1} * c^l * z' * z'}$, effective filter size $z * z$, pooling size $s * s$.

Output: Output image $I^{l+1} \epsilon R^{nc^{l+1} * w^{l+1} * h^{l+1}}$, with $n = \frac{(z'-z+1)^2}{s^2}$.

function DOUBLE CONVOLUTION

1. $I^l \leftarrow IdentityMatrix(c^l z^2)$;
2. Reorganize I^l to shape $c^l z^2 * c^l * z * z$;
3. $\tilde{W}^l \leftarrow W^l * I^l$; /* output shape: $c^{l+1} * c^l z^2 * (z' - z + 1) * (z' - z + 1)$ */
4. Reorganize $\tilde{W}^l$ to shape $c^{l+1}(z' - z + 1)^2 * c^l * z * z$;
5. $O^{l+1} \leftarrow I^l * \tilde{W}^l$; /* output shape: $c^{l+1}(z' - z + 1)^2 * w^{l+1} * h^{l+1}$ */
6. Reorganize O^{l+1} to shape $c^{l+1} w^{l+1} h^{l+1} * (z' - z + 1) * (z' - z + 1)$;
7. $I^{l+1} \leftarrow pool_s(O^{l+1})$; /* output shape: $c^{l+1} w^{l+1} h^{l+1} * \frac{z'-z+1}{s} * \frac{z'-z+1}{s}$ */
8. Reorganize I^{l+1} to shape $c^{l+1}(\frac{z'-z+1}{s})^2 * w^{l+1} * h^{l+1}$;

end function

1	0	0	0	0	0	0	0
0	1	0	0	0	0	0	0
0	0	1	0	0	0	0	0
0	0	0	1	0	0	0	0
0	0	0	0	1	0	0	0
0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	1

Identity (8x8)

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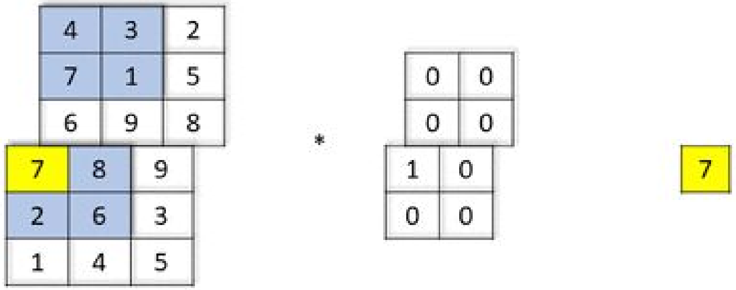
end function

Applying All 8 Masks for fix position



Meta Filter (2x3x3)
Filter (2x2x2) (Blue)

Rearranged 1st Row

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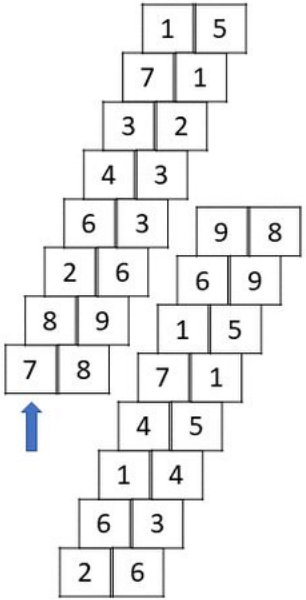
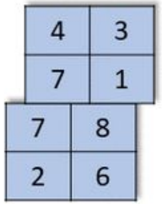


Rearranging



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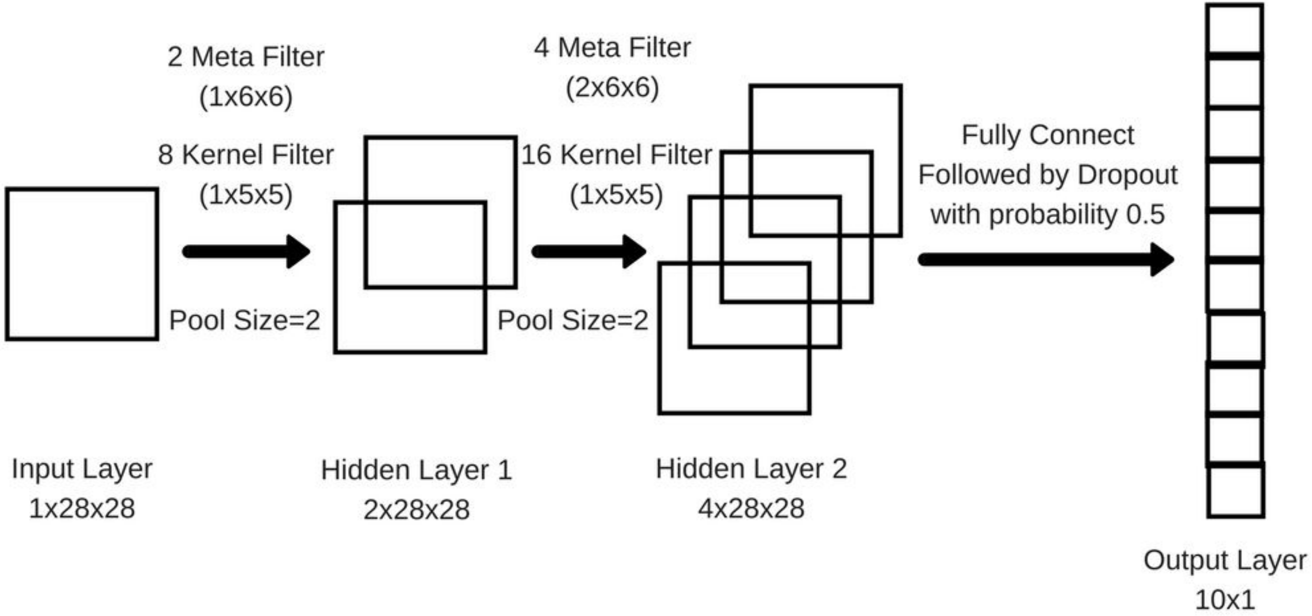
end function

IMPLEMENTATION & RESULTS

Architecture



Variants of DCNN

Standard CNN

$z' = z$

DCNN is generalisation of CNN

Concat DCNN

$s = 1$

Maximally parameter efficient

With the same amount of parameters produces $\frac{(z'-z+1)^2 z^2}{z'^2}$ times more channels for a single layer.

Maxout DCNN

$s = z' - z + 1$

Output image channel size equal to the number of meta filters.

Yields a parameter efficient implementation of maxout network.

Meet Alberto.

He recently moved from Spain to a small town in Northern Ireland.

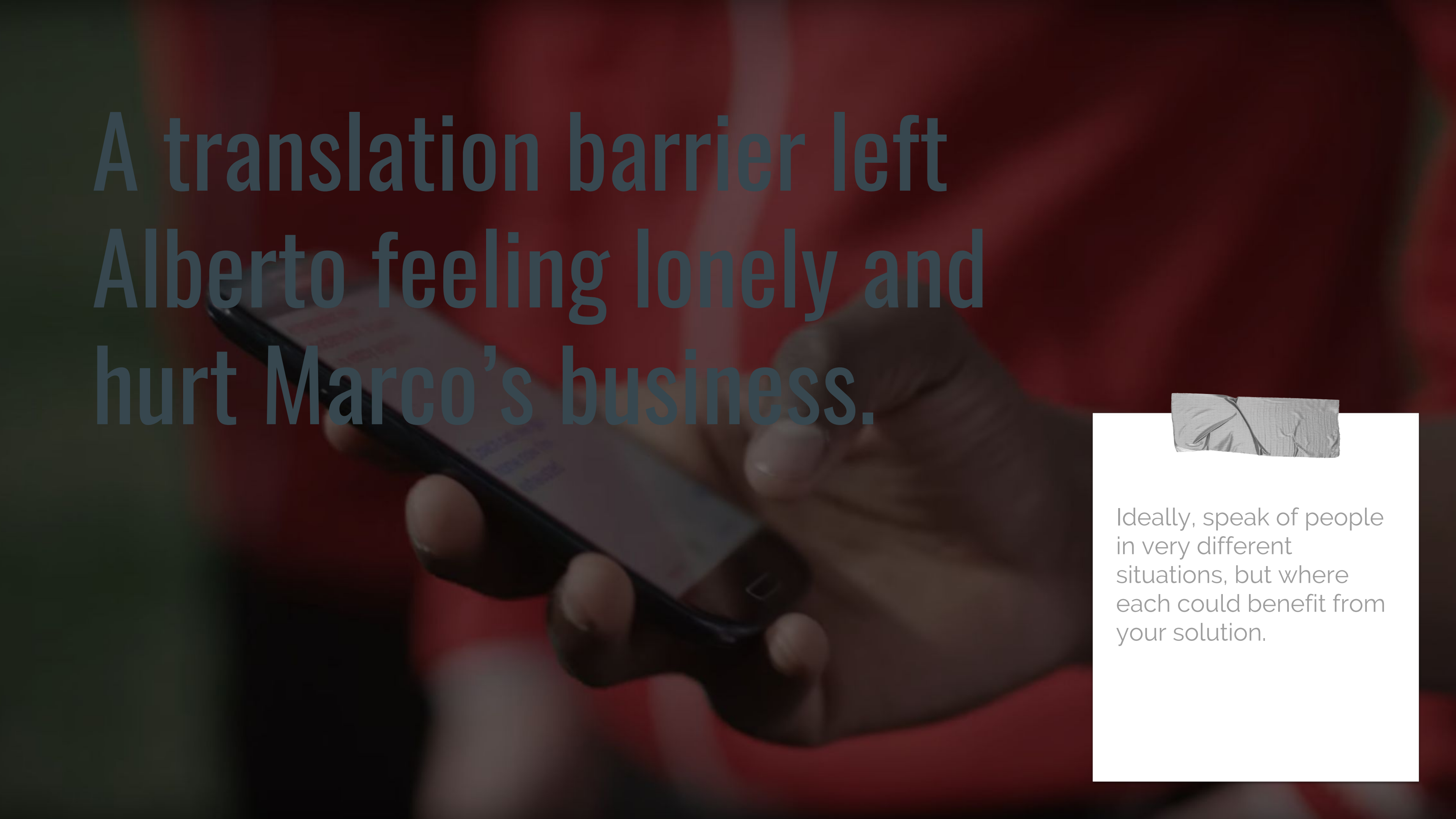
He loved soccer, but feared he had no way to talk to a coach or teammates.

Meet Marcos.

He recently opened a camera shop near the Louvre in Paris.

Visitors to his store, mostly tourists, speak many different languages making anything beyond a simple transaction a challenge.

Story for illustration purposes only



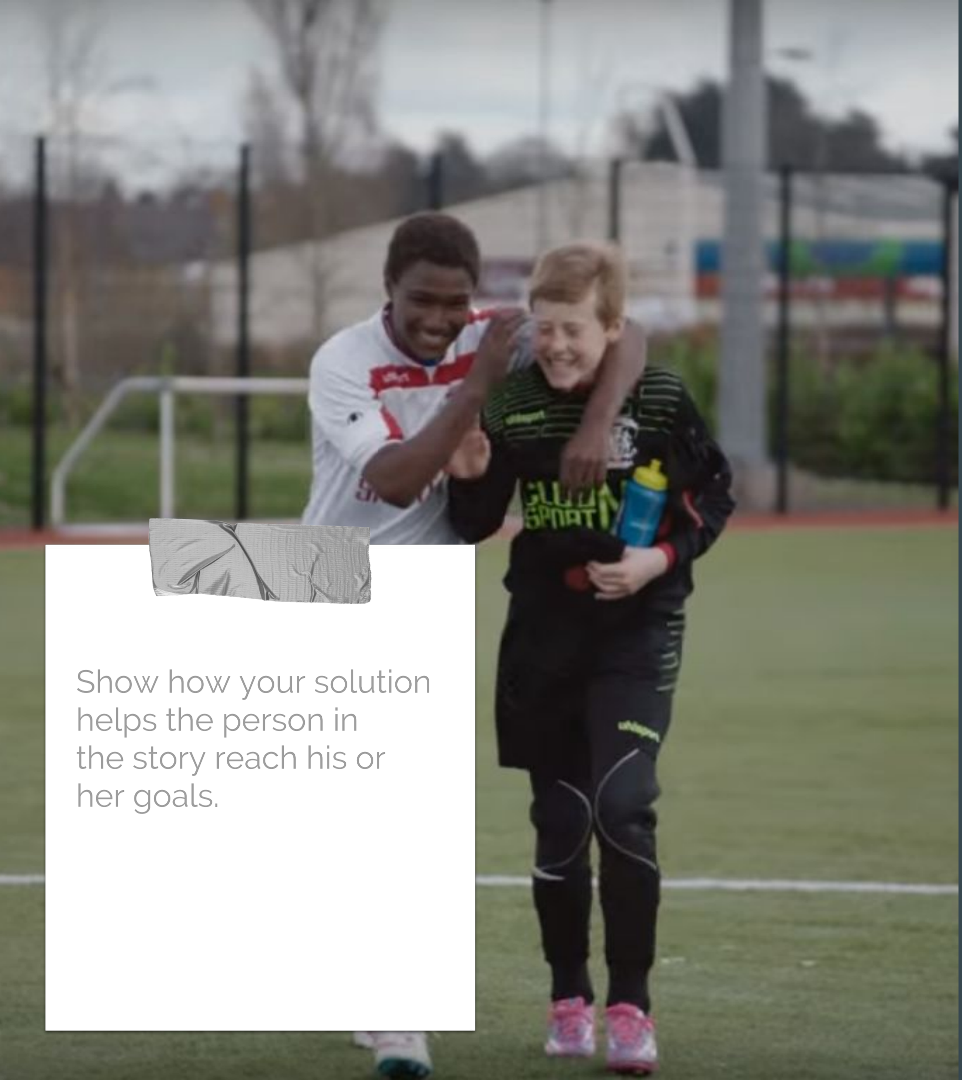
A translation barrier left Alberto feeling lonely and hurt Marco’s business.

Ideally, speak of people in very different situations, but where each could benefit from your solution.

Then, Marcos discovered Google Translate

He has his visiting customers speak their camera issues into the app.

He’s able to give them a friendly, personalized experience by understanding exactly what they need.



Show how your solution helps the person in the story reach his or her goals.

A simple gesture

Coaches Gary and Glen knew no Spanish.

They used Google Translate to invite Alberto to join in… "Do you want to play?"… "Can you defend the left side?"

From outsider to star

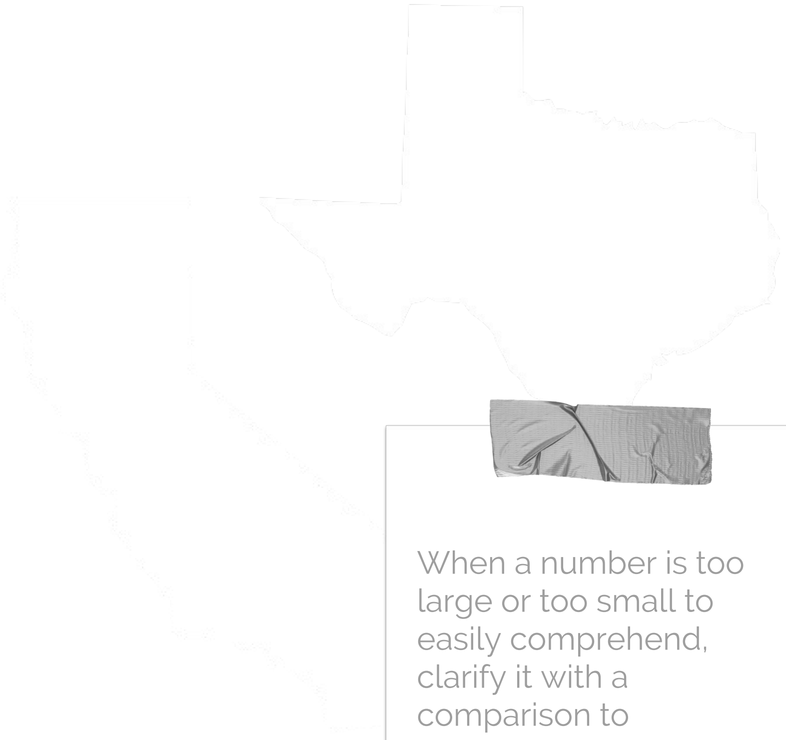
Alberto scored 30 goals in 21 games. He is now being scouted by several professional clubs in the Premier League. And he's a favorite of the other boys on the team.

See a short video on Alberto's story

Stories become more credible when they use concrete details such as the specific complex moves Alberto learned through Translate and his 30 goals in 21 games performance stats.

More than 50 million Americans travelled abroad in 2015

THAT'S MORE THAN THE POPULATION OF CALIFORNIA AND TEXAS COMBINED



When a number is too large or too small to easily comprehend, clarify it with a comparison to something familiar.

Source: travel.trade.gov

4. Closing

Build confidence around your product or idea by including at least one of the these slides:

What has been accomplished and what might be left to tackle?

Who supports your idea (or doesn't)?

How can the audience get involved or find out more?

Milestones

October 2014

Translate web pages with Chrome extension

October 2015

Translate text within an app

2014

August 2015

Translate conversations through your Android watch

November 2015

Translate written text from English or German to Arabic with the click of a camera

Know a 2nd language?
Make Google Translate even better by joining the community.

Inspire your audience to act on the information they just learned.

Depending on your idea, this can be anything from downloading an app to joining an organization.