# Deep Learning for Digital Geometry Processing and Analysis: A Review

基於深度學習的數位幾何處理與分析技術研究進展

Xia Qing, Li Shuai, Hao Aimin, Zhao Qinping

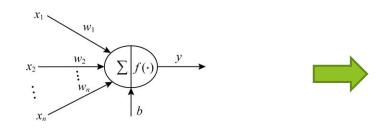
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- ▶ 相關深度學習模型
- ▶ 面向深度學習的幾何資料表示
- ▶ 基於深度學習的數位幾何處理
- ▶ 總結與展望

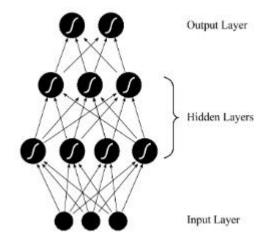
# 相關深度學習模型

- Neural networks
- Convolutional neural net-work
- Generative adversarial network
- Recurrent neural network
- Others. like DBN (deep belief network), AE (AutoEncoder)

#### Neural networks

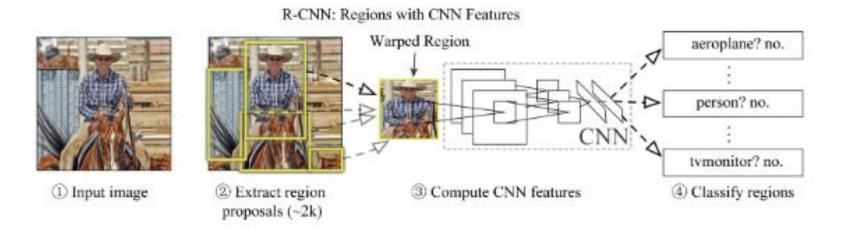


A typical neuron in neural networks

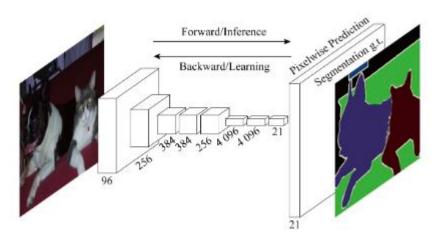


A typical multi-layer neural network model

#### convolutional neural net-work



Object detection based on R-CNN



Detection Heatmaps +
Associative Embeddings

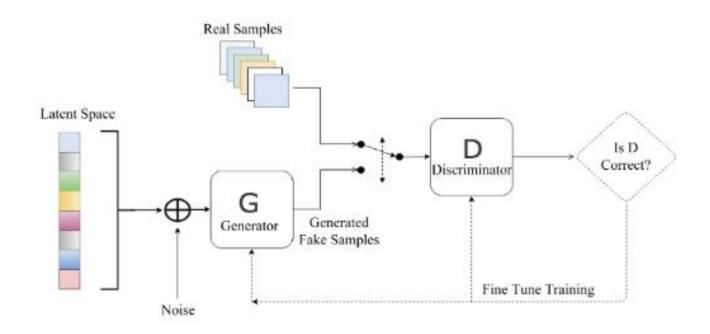
Final Prediction

Right Wrist Left Knee

Architecture of FCN

**Associative Embedding** 

# generative adversarial network



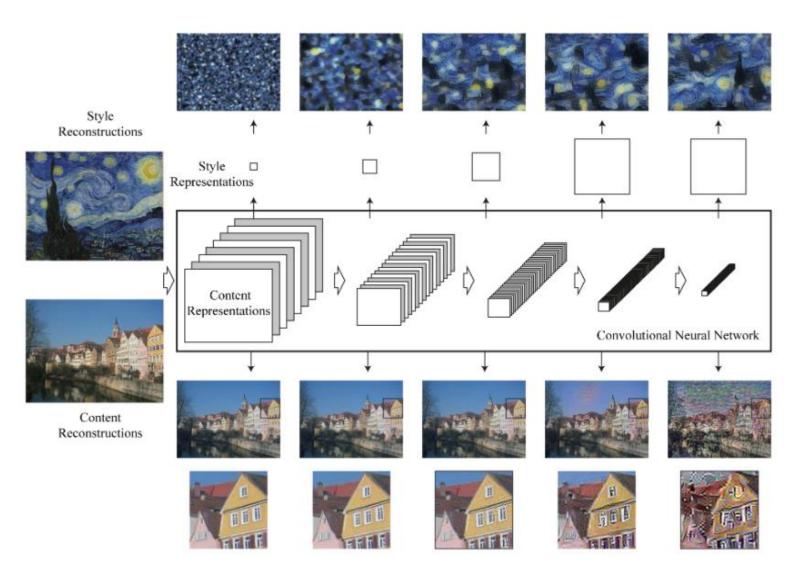
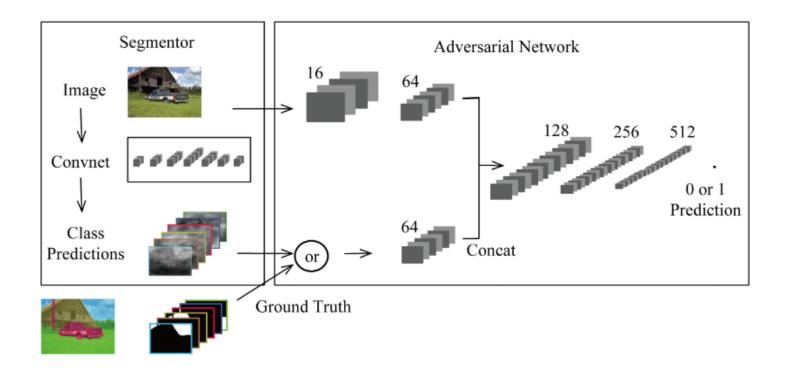
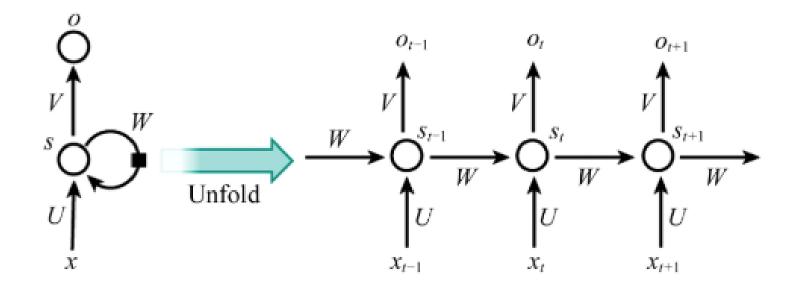


Image style transfer using convolutional neural networks



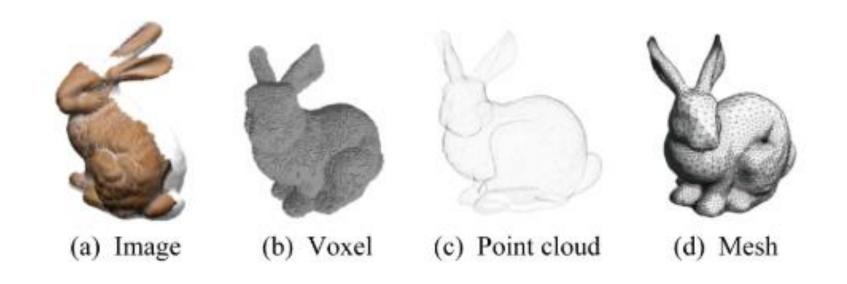
Semantic segmentation using adversarial networks

## recurrent neural network

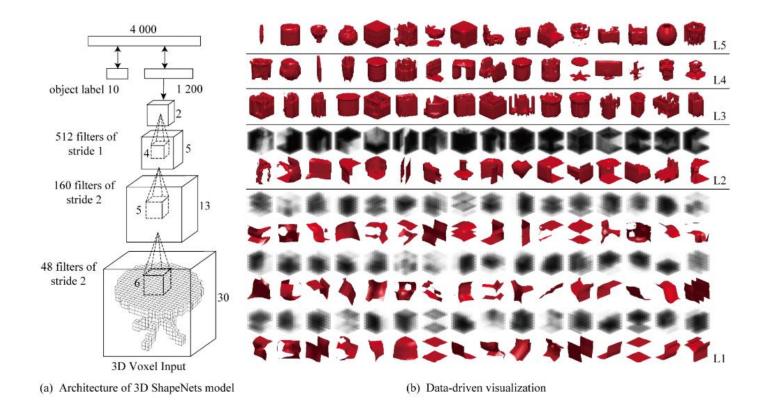


Architecture of RNN

# 面向深度學習的幾何資料表示

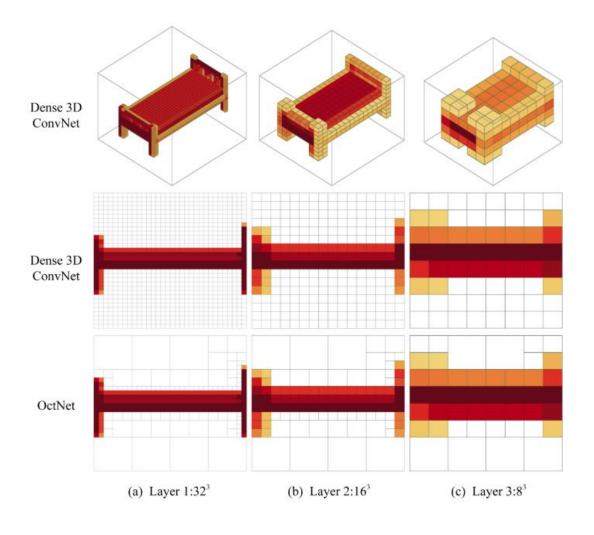


- ▶ 3D ShapeNets: A deep representation for volumetric shapes
- VoxNet: A 3D convolutional neural network for real-time object recognition
- ▶ Volumetric and multi-view CNNs for object classification on 3D data



3D object recognition based on voxel representation and deep model

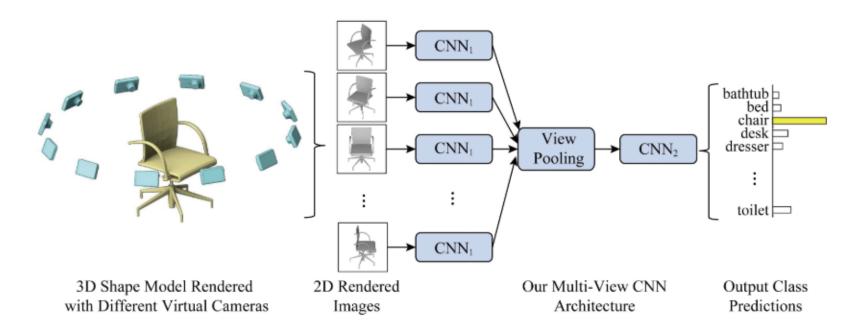
- Volumetric 3D mapping in real-time on a CPU
- OctNet: Learning deep 3D representations at high resolutions
- O-CNN: Octree-based convolutional neural networks for 3D shape analysis
- Octree generating networks: Efficient convolutional architectures for high-resolution 3D outputs
- ► Hierarchical surface prediction for 3D object reconstruction



Voxel representation based on Octree

## Multi-view image

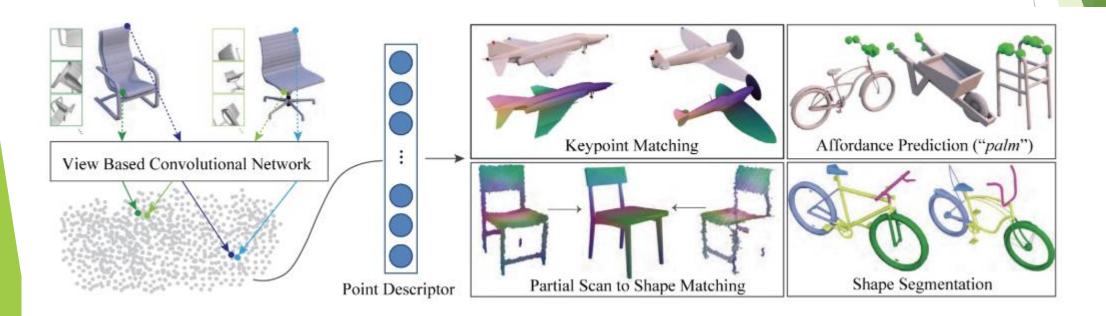
- ▶ Image-guided 3D model labeling via multiview alignment
- Multi-view convolu-tional neural networks for 3D shape recognition



Learning multi-view feature fusion using CNN

## Multi-view image

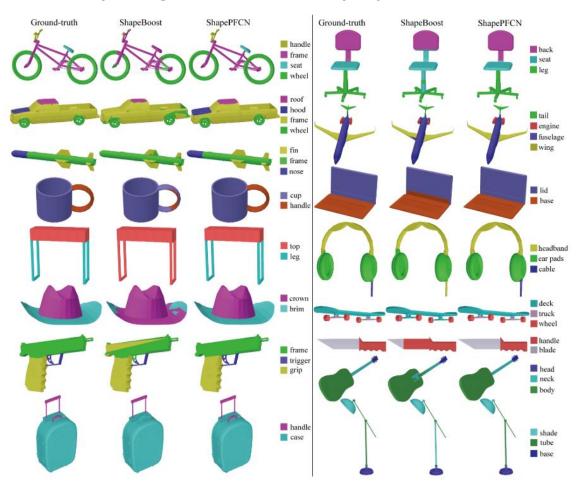
Learning local shape descriptors from part correspondences with multiview convolutional networks



Extraction of local shape descriptor using images from local and global views

# Multi-view image

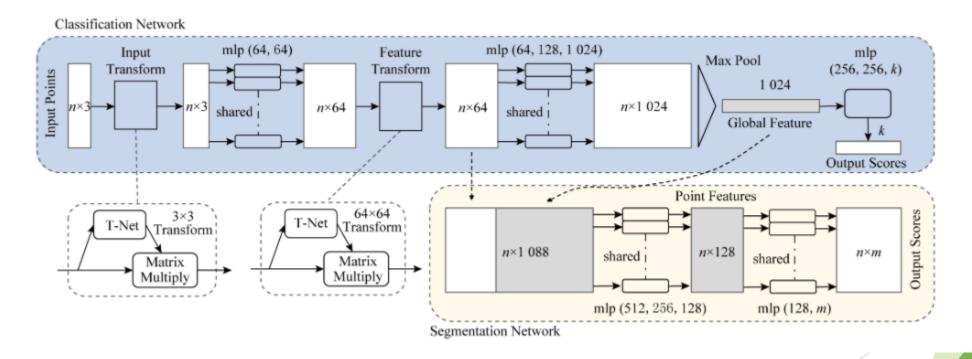
▶ 3D shape segmentation with projective convolutional networks



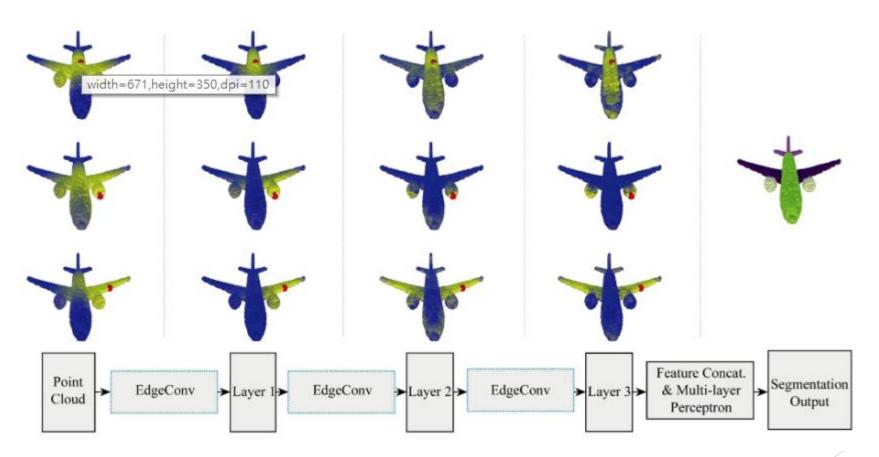
Point

Gragh

- ▶ PointNet: Deep learning on point sets for 3D classification and segmentation
- ▶ PointNet++: Deep hierarchical feature learning on point sets in a metric space



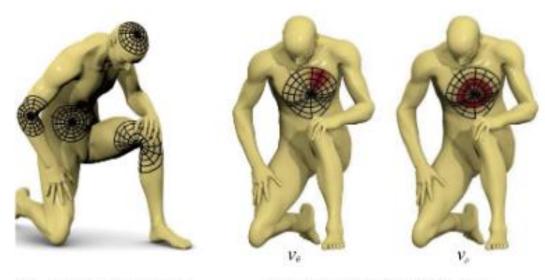
- ► A new model for learning in graph domains
- The graph neural network model
- Spectral networks and locally connected networks on graphs
- ▶ 3D graph neural networks for RGB-D semantic segmentation
- SyncSpecCNN: Synchronized spectral CNN for 3D shape segmentation
- ► RGCNN: Regularized graph CNN for point cloud segmentation
- Dynamic graph CNN for learning on point clouds



Architecture of DynGCNN

- Gragh
- Manifolds
- Traditional descriptor

- ► Geodesic convolutional neural networks on riemannian manifolds
- ► ShapeNet: Convolutional neural networks on non-euclidean manifolds



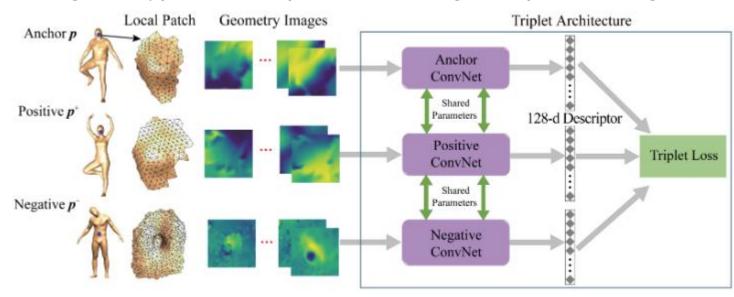
(a) Examples of local geodesic patches

(b) Example of angular and radial weights

Geodesic polar system built on mesh surface

- Learning shape correspondence with anisotropic convolutional neural networks
- Learning class-specific descriptors for deformable shapes using localized spectral convolutional networks
- Geometric deep learning on graphs and manifolds using mixture model CNNs

- ➤ 3D mesh labeling via deep convolutional neural networks (curvature (CUR), PCA feature (PCA), shape diameter function (SDF), distance from medial surface (DIS), average geodesic distance (AGD), shape context (SC), and spin image (SI))
- Jointly learning shape descriptors and their correspondence via deep triplet CNNs
- Learning 3D keypoint descriptors for non-rigid shape matching



Extraction of high-level features using local low-level features

# 基於深度學習的數位幾何處理

- ▶ 模型匹配與檢索
- ▶ 模型分類與分割
- ▶ 模型生成
- ▶ 模型修復與重建
- ▶ 模型變形與編輯

Dense human body correspondences using convolutional networks

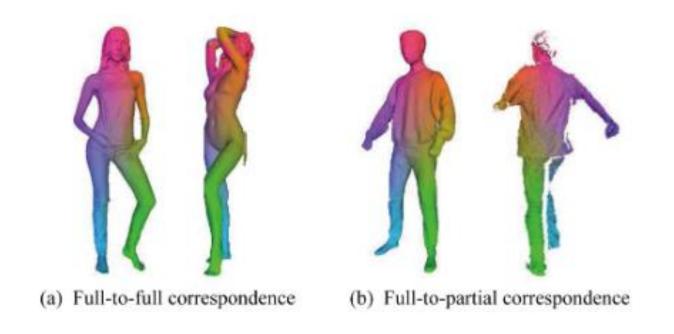
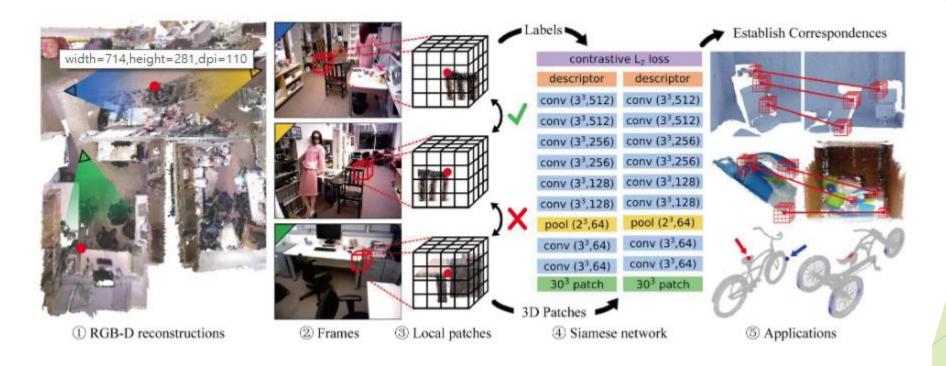


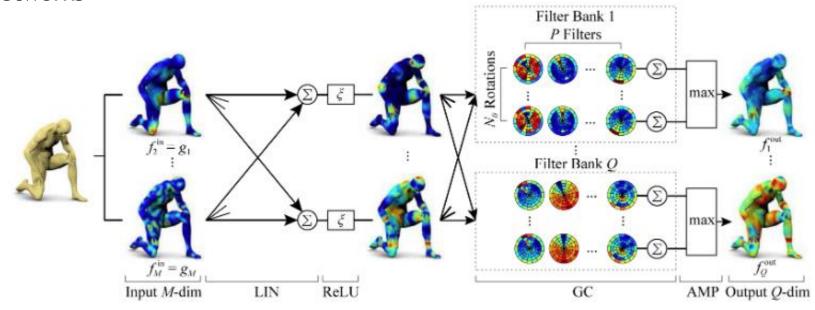
Illustration of shape correspondence

▶ 3Dmatch: Learning local geometric descriptors from RGB-D reconstructions



Key-point matching based on voxel representation

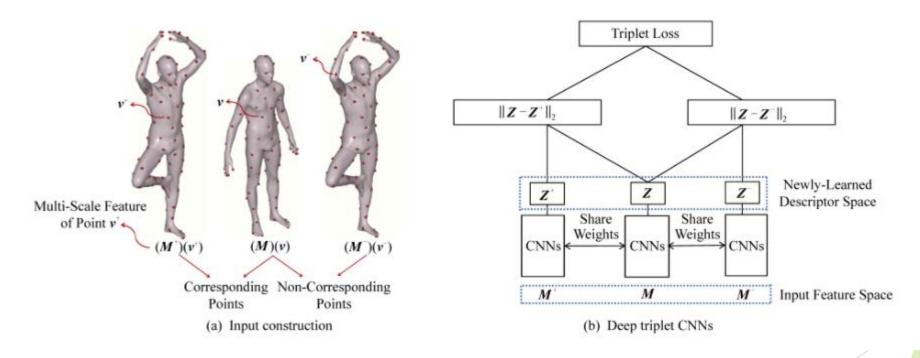
Learning shape correspondence with anisotropic convolutional neural networks



Shape correspondence based on Geodesic CNN

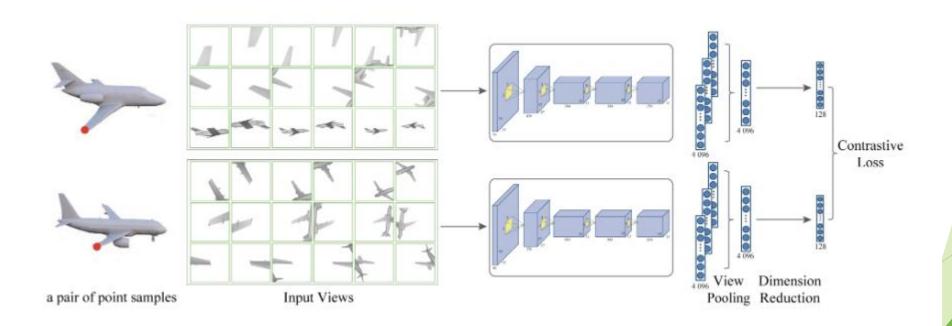
Deep functional maps: Structured prediction for dense shape correspondence

- ▶ A method of 3D model retrieval by the spatial distributions of components
- Jointly learning shape descriptors and their correspondence via deep triplet CNNs



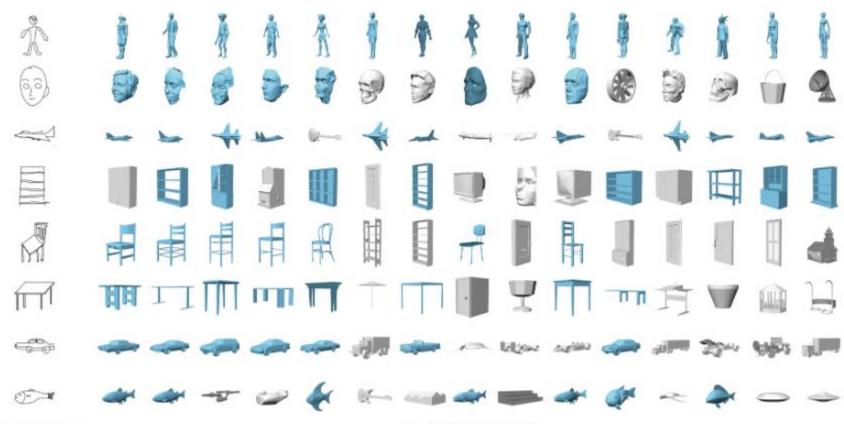
shape matching based on deep triplet CNN

- Learning local shape descriptors from part correspondences with multiview convolutional networks
- Learning part-in-whole relation of 3D shapes for part-based 3D model retrieval



Multi-scale shape matching based on multi-view images

- Deep correlated metric learning for sketch-based 3D shape retrieval
- Sketch-based 3D shape retrieval using convolutional neural networks



- Convolutional-recursive deep learning for 3D object classification
- Learning rich features from RGB-D images for object detection and segmentation
- Multimodal deep learning for robust RGB-D object recognition
- ► A deep representation for volumetric shapes
- VoxNet: A 3D convolutional neural network for real-time object recognition

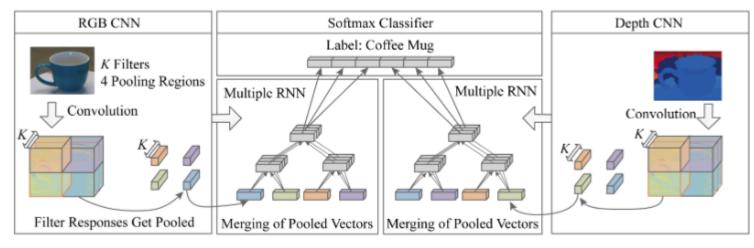
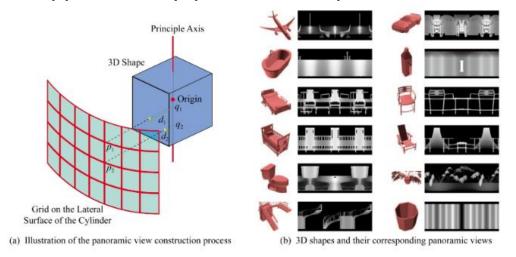


Fig. 30 3D object recognition based on RNN<sup>[84]</sup>

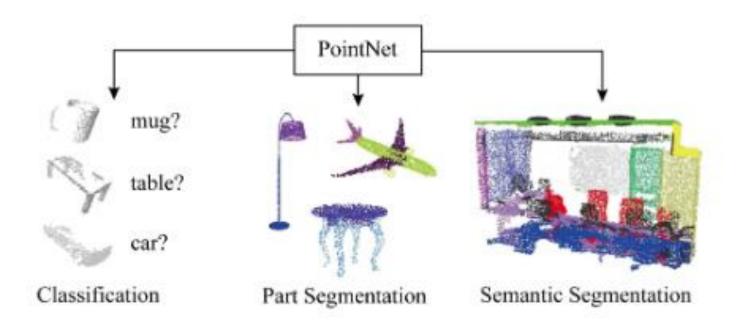
Deeppano: Deep panoramic representation for 3-D shape recognition



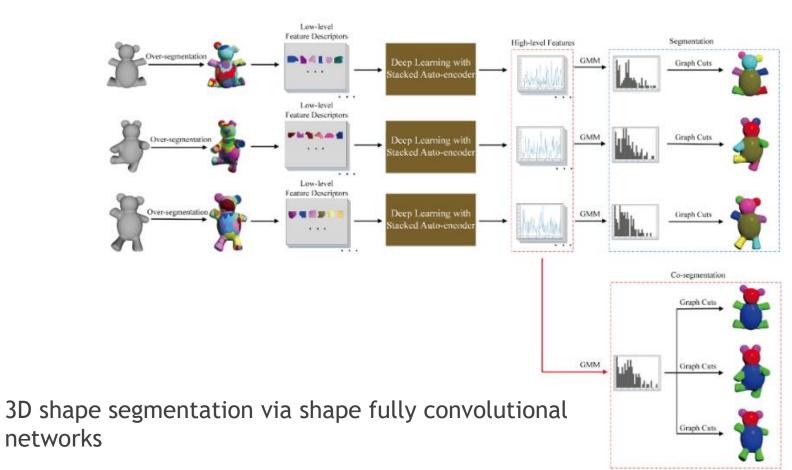
Predictive and generative neural networks for object functionality



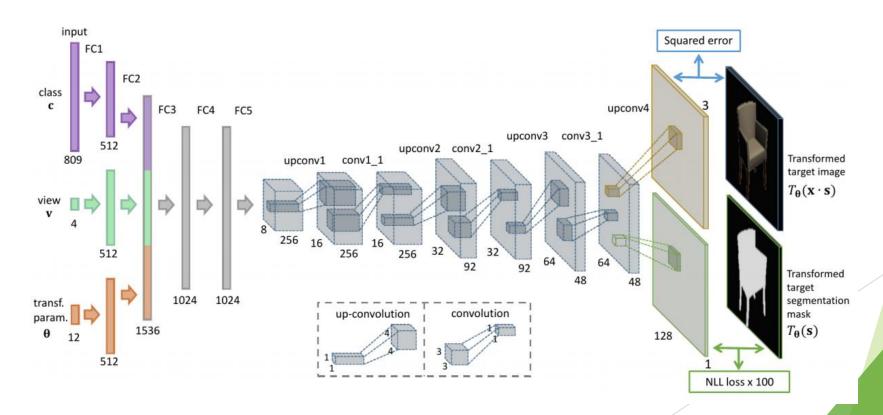
- ▶ PointNet: Deep learning on point sets for 3D classification and segmentation
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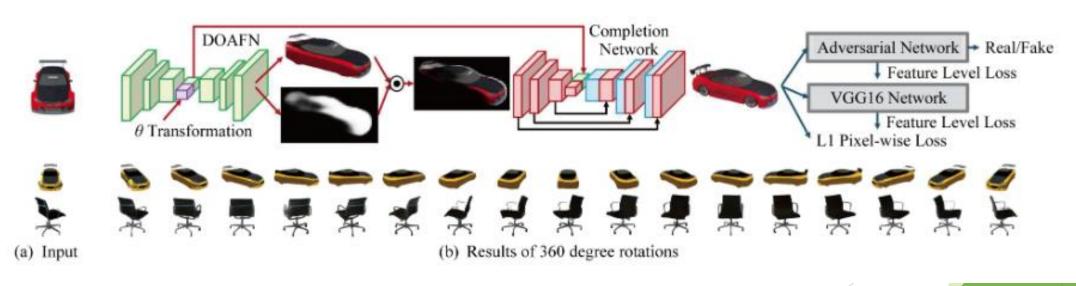
- ▶ 3D mesh labeling via deep convolutional neural networks
- Unsupervised 3D shape segmentation and co-segmentation via deep learning



- Transforming auto-encoders
- Deepstereo: Learning to predict new views from the world's imagery
- ► Learning to generate chairs, tables and cars with convolutional networks



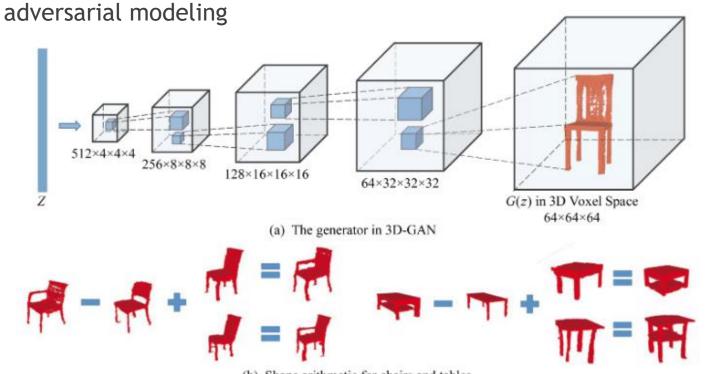
- Spatial transformer networks (STN)
- View synthesis by appearance flow
- Transformation-grounded image generation network for novel 3D view synthesis



Multi-view images generated from a single view image

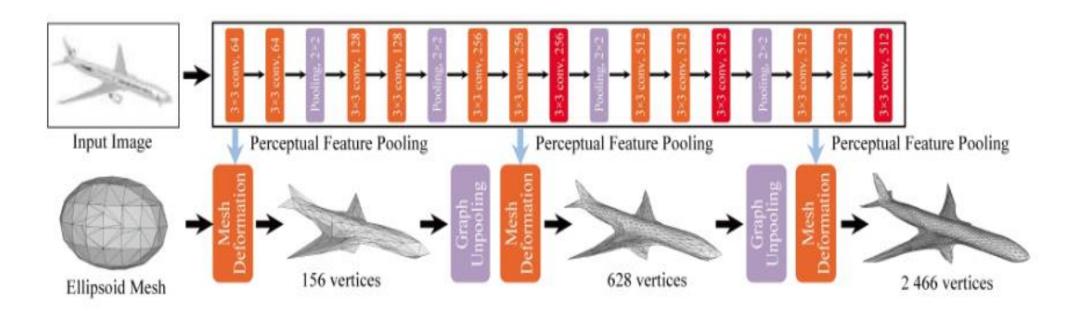
Learning a predictable and generative vector representation for objects

Learning a probabilistic latent space of object shapes via 3D generative-



(b) Shape arithmetic for chairs and tables

▶ Pixel2Mesh: Generating 3D mesh models from single RGB images

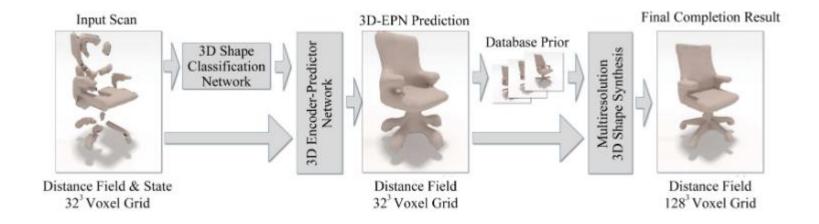


Deform an coarse ellipsoid mesh into a refined mesh using CNN

- Transforming auto-encoders
- Deepstereo: Learning to predict new views from the world's imagery
- ▶ Learning to generate chairs, tables and cars with convolutional networks

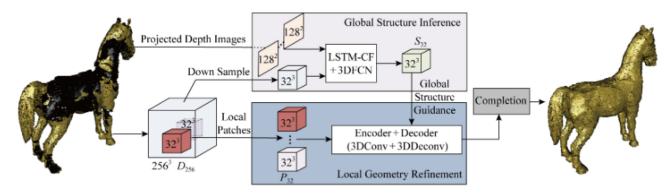
- Transforming auto-encoders
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Shape completion using 3D-encoder-predictor CNNs and shape synthesis

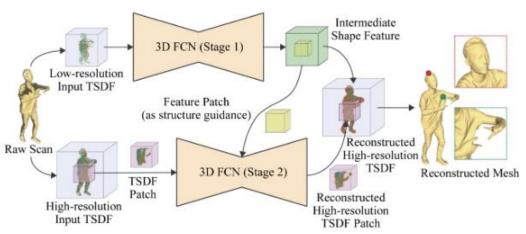


Shape inpainting using 3D generative adversarial network and recurrent convolutional networks

 High-resolution shape completion using deep neural networks for global structure and local geometry inference

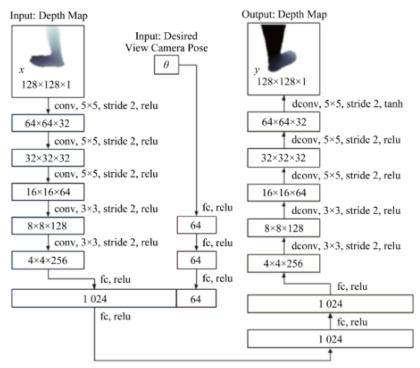


Learning to reconstruct high-quality 3D shapes with cascaded fully convolutional networks

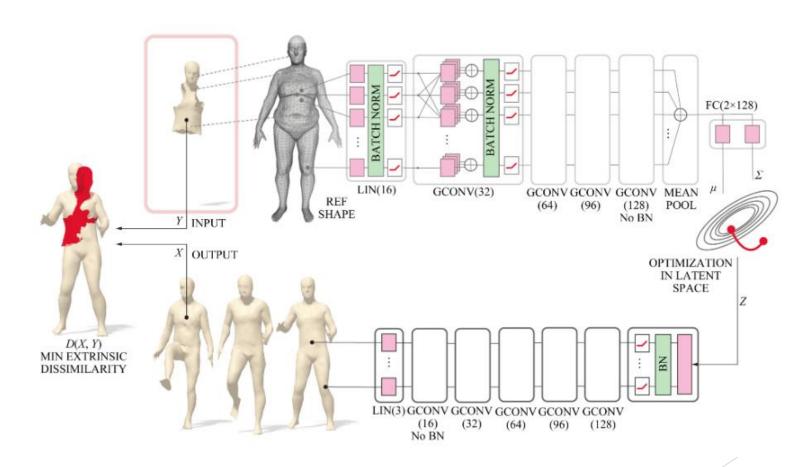


Point cloud completion of foot shape from a single depth map for fit matching using deep learning view synthesis

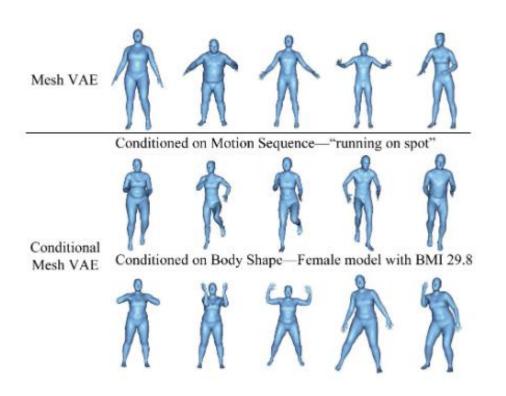
 Deep learning anthropomorphic 3D point clouds from a single depth map camera viewpoint

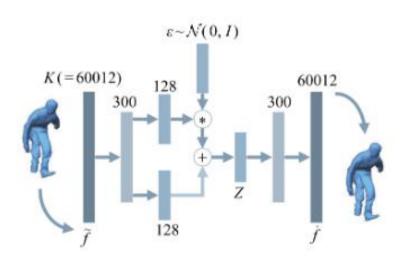


Deformable shape completion with graph convolutional autoencoders



Variational autoencoders for deforming 3D mesh models





▶ Biharmonic deformation transfer with automatic key point selection

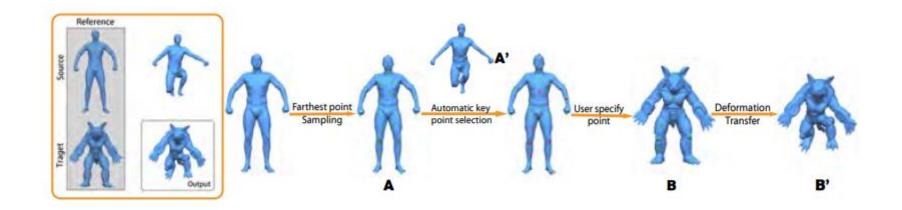
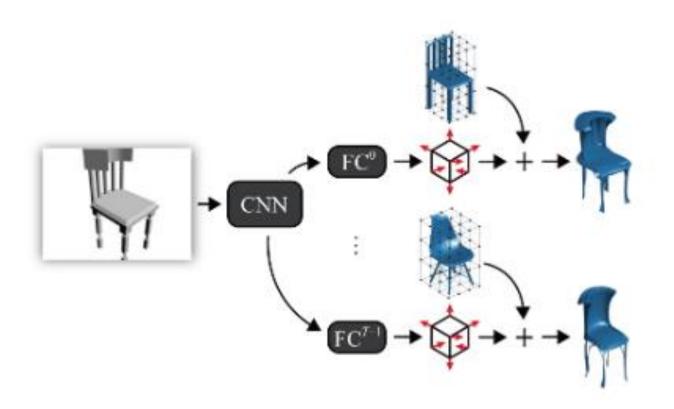


Figure 1: The pipeline of our algorithm.

Learning free-form deformations for 3D object reconstruction



- Analogy-driven 3D style transfer
- Learning detail transfer based on geometric features



(a) Input (target) mesh without details

(b) Details from each source mesh (blue) are synthesized on the target mesh (pink)

Functionality preserving shape style transfer



#### 總結與展望

#### 優勢

- □ 相比于傳統的分析和處理方法,具有強大的資料抽象特徵提取能力
- □ 極大地提高了模型的各方面應用上性能和效率

#### ~ 不足

- □ 沒有統一的資料表示
- □ 缺乏大規模公開資料集
- □ 網路結構缺乏針對性